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Development of Driving Simulation Framework for Defining the Operational Design Domains of Autonomous Vehicles in Rural and Urban Environments

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Development of Driving Simulation Framework for Defining the Operational Design Domains of Autonomous Vehicles in Rural and Urban Environments

by

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Dedication

Dedicado a mis padres, por enseñarme el valor de la escuela y haberme apoyado para alcanzar mis metas. También a mi comunidad, Chaparral, NM, que siempre será mi hogar, no importa donde viva.

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Abstract

Development of Driving Simulation Framework for Defining the Operational Design Domains of Autonomous Vehicles in Rural and Urban Environments

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Advanced Driver Assistance Systems (ADAS) have been rapidly improving over the last decade with the implementation of more automated features. This will lead to the development of fully autonomous vehicles (AVs) and their deployment into the traffic stream. Although the idea of self-driving cars in society is inevitable, there is much more research that needs to be done before that becomes a reality. Therefore, a transition phase will first occur in which traffic will consist of a mixed configuration of various automated and human-driven vehicles. This will undoubtedly result in consequences as the different levels of AVs and human drivers interact in various roadway environments and distinct traffic characteristics. For that reason, it is imperative to research the full capabilities of all levels of automation and understand their limitations based on the diverse set of roadway environments and various driving scenarios that will be encountered. In this thesis, an attempt was made to begin understanding the capabilities and limitations of AVs in mixed traffic. Given the multitude of environments and scenarios, prioritization was given to a situation that would be common for Texas roadways. Therefore, this thesis develops a driving simulation environment to understand the performance of AVs with respect to traffic safety and efficiency in Texas rural highways and urban roads during a forced lane drop scenario and a merging vehicle maneuver. This prioritization was used to begin establishing the operational design domains (OODs) of AVs, which will be crucial in mitigating the risk that will arise during the interactions of different levels of AVs and humans. Preliminary results from Driver-In-the-Loop (DIL) experiments seem to suggest that increasing the level of automation might have some benefits for traffic as a whole but that lower-level AVs might led to some dangerous situations for human drivers. More human participants will be needed to verify these results but overall, this thesis managed to develop a feasible simulation framework that can be used for future human subject studies.

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Chapter 1: Introduction

Automobiles have gone through various changes throughout its history and with the rapid advancement of technology, more and more automated features have been incorporated to assist with driving. This has led to the development of Advanced Driving Assistance Systems (ADAS) such as Automatic Emergency Braking, Lane Departure Warning, Parallel Parking Assistance, and others. The implementation of ADAS has drastically changed the driving experience but more advances to the automobile are still to come, specifically the development of fully Autonomous Vehicles (AVs) and Connected Autonomous Vehicles (CAVs). Even now, the current state of AVs is having an impact on driving, with the incorporation of low-level automation such as Adaptive Cruise Control (ACC) and Lane Changing. With partially autonomous features already being commercialized, and research rapidly advancing, it is inevitable that our society will see increasing level of vehicle automation. Still, this transition is bound to come with its own set of risks and it is therefore imperative to get a proper understanding of the capabilities of all ADAS features, especially the limitation that they may have in different environments.

PURPOSE OF RESEARCH

The development of AVs and CAVs will have a profound effect, not only on the automotive industry, but throughout all of the society. Still, there is some uncertainty over when fully functional AVs will be incorporated into traffic, with some studies forecasting an adoption of 24.8% for Level 4 AVs by 2045.[1] Therefore, a long transitional phase is expected to first take place in which traffic will be configured by a mixture of partially

[1]Bansal and Kockelman, "Forecasting adoption of autonomous vehicles," 2017.

autonomous vehicles and human drivers. This could lead to confusion on how AVs and human drivers are supposed to interact and might result in more accidents and a reduction in traffic efficiency. For that reason, it is imperative to distinguish between the environments and scenarios that are drivable for each level of automation, and which are beyond their capabilities.

To assess the limitation of AVs in relation to traffic density and ADAS parametrization, a proper understanding of each level of automation in different environments and scenarios is required. Therefore, the purpose of this study was to analyze the performance of AVs in different circumstances with Driver-In-the-Loop (DIL) simulations and begin establishing a proper definition of their Operational Design Domains (ODDs). DIL simulations were used to develop realistic virtual environments, vehicle models, and test ADAS and AV technology in a safe and affordable way while also producing high quality results. Also, through DIL simulation, unique scenarios that incorporate human subjects and produce an accurate depiction of AV-human interactions could be repeatedly tested, as opposed to field experiments.

This simulation-based approach to analyze ADAS will give some clarity into their capabilities and will allow interested parties to prepare throughout the transitional phase before fully autonomous vehicles are completely adopted. With an emphasis given on traffic safety, this work will also help government agencies take the necessary steps to mitigate the problems that will be encountered in a mix traffic environment, and start considering the implementation of new regulations or improvements on road infrastructure.

DEFINING OPERATIONAL DESIGN DOMAINS (ODDS)

The proper deployment of AVs requires a detailed framework by which industries, academia, government agencies, and the public can rely on. For this reason, a clear definition of AV's operational design domains (ODDs) is crucial. From SAE J3016, ODDs are defined as, "operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environment, geographical, and time-of-day restrictions, and/or requisite presence or absence of certain traffic or roadway characteristics."[2] In essence, an ODD framework will give a proper description of the full range of capabilities that all levels of AVs have, categorizing circumstances as either drivable or dangerous. With this type of categorization, a pre-defined operational domain can be programmed within AVs to enable its autonomous features only when it is considered safe. Otherwise, a proper warning of a dangerous situation should be given to human drivers and require them to take over.

Given the definition of an ODD, a proper framework should include, but not be limited to, information on traffic characteristics, roadway geometry, infrastructure quality, weather conditions, and driving behavior. There are countless characteristics that can be analyzed to begin defining AV's capabilities. Therefore, it is more effective to first prioritize common roadways and driving scenarios to begin establishing the foundation of the ODD framework.

Prioritized Environments

Currently, Original Equipment Manufacturers (OEMs) do not identify all the regions that their automated features are capable of driving in. Instead, the specific environment and constraints are initially identified, with the intention of designing a system to only operate within the pre-established criterion.[3] Although this workflow allows OEMs to clearly establish an ODD for their Automated Driving Systems (ADS), they are very

[2]SAE, "Taxonomy and definition," 2018.
[3]Lee et al., "Identifying Operational Design Domains," 2020.

rigid definitions that do not work for the variability that real driving brings. Still, with a multitude of roadways, all consisting of their own distinct characteristics, it is a challenging task to categorize the capabilities of AVs for every unique environment. Therefore, it would be more beneficial to first prioritize the most common roadway environments throughout a particular region and define the capabilities of ADS based on these roadways and their unique features, including their geometric design and traffic characteristics. For this study, it was decided to emphasize the analysis of ADS on roadway environments that would resemble those of the state of Texas.

Texas is a large state with a diverse landscape and the largest highway system, consisting of about 680,000 lane miles.[4] This equips it with a vast set of options for testing and categorizing the capabilities of AVs on different environments. From countless options available, it was decided to primarily focus on Texas' highways and urban roads, which would allow for an in-depth performance analysis of AVs on varying levels of complexity. Highways are simplistic with fewer lanes, lighter traffic, and repetitive infrastructure patterns. In contrast, urban roads tend to have a high degree of complexity, usually having multiple lanes, higher traffic density, and involving unpredictable behavior from drivers, pedestrians, and cyclists. Within Texas there is some variability in the design of highways, such as Diamond, Cloverleaf, or X-Configuration Interchange patterns. It was decided to focus only on the X-Configuration Interchange pattern for a rural highway environment, as it a simple roadway that is prevalent through all of Texas. As for the urban environment, the typical design of an urban city with a construction zone area was used for this study. These two environments allow for an adequate variability in the level of complexity which can be used to best analyze the performance of AVs.

[4] U.S. Department of Transportation Federal Highway Administration. "Highway Statistics 2017." 2018.

Problematic Driving Scenarios

The roadway environment is a key part in analyzing an AV's performance and understanding what their limitations are. But it is equally important to understand how well they perform in different driving scenarios. Given that there are countless circumstances that can happen on the road, it is impossible to completely analyze all the driving scenarios that an AV will encounter. Still, there are specific situations that can be prioritized to better understand the capabilities of AVs. The most critical type of scenarios that require special focus are edge cases, which are considered problematic driving situations that involve a higher level of complexity. By focusing on how well AVs perform in these problematic scenarios, a clear ODD framework can be established to identify these situations and incorporate limitations that will mitigate the risk of crashes.

For this study, two different driving scenarios were selected for analyzing AV safety and traffic performance on both highways and urban roads. The first scenario was a forced lane change maneuver, which typically consist of a lane drop that forces drivers to merge to an adjacent lane. The second scenario was a merging vehicle maneuver, where an adjacent vehicle merges directly in front of a driver's path of travel. Although these two scenarios are very common in everyday driving, they can be problematic for some AV systems and could drastically affect their performance. By analyzing AVs behaviors in these driving scenarios, a better understanding of how they deal with typical driving maneuvers will lead to a more robust definition of their operational domains.

Chapter 2: Literature Review

The advancement in computation, in combination with a reduction of cost for hardware has allowed for the rapid development of ADAS. This area is continuously progressing as improvements in hardware and software are integrated into vehicles. Today, the capabilities of these systems are more advanced than ever, containing a multitude of features and controls. With so much technology integrated into vehicles, it can be difficult to distinguish what constitutes as an AV, and what is the difference between each level of automation. The following sections will attempt to clarity the distinctions and give details on the technology that is used to produce autonomous driving capabilities. Also, a description will be given on the use of simulation-based testing, specifically Driver-In-the-Loop Simulation, which is a key part of was of analyzing the performance of different levels of AVs.

Defining Advanced Driving Assistance Systems (ADAS)

As autonomous features started being incorporated into automobiles, a proper distinction of an AV and a conventional human-driven vehicle (HDV) was needed. Therefore, various state legislatures and engineering organizations began developing the standard definition of what would be considered an AV and an HDV. The definition of a conventional HDV is “A vehicle designed to be operated by a conventional driver during part, or all of, every trip.”[5] As for AVs, there are different terms and definitions used by different organization and states. The most common terms used are autonomous vehicles and fully autonomous vehicles, which have been defined by most states as a vehicle equipped with an automated driving system (ADS) that can operate the vehicle without

[5] SAE, 2018.

human intervention.[6] Others tend to use a similar definition but differ in the terminology, such as SAE and the state of Tennessee, which use the terms ADS-operated vehicles and ADS-dedicated vehicles (ADS-DV), respectively.[7] Rarely, some differing term and definition will be used, such as in the state of Iowa, which use the term, driverless capable vehicle, and define it as "a system-equipped vehicle capable of performing the entire dynamic driving task within the automated driving system's operational design domain, if any, including but not limited to achievement of a minimal risk condition without intervention or supervision by a conventional human driver."[8]

For an AV to operate as a human driver, its automated system is required to perform specific tasks. From SAE, these tasks are called dynamic driving tasks, and are defined as "All of the real-time operational and tactical functions required to operate a vehicle in on-road traffic, excluding the strategic functions such as trip scheduling and selection of destinations and waypoints."[9] This gives a general description of what an AV should be capable of, but a much more detailed categorization has been developed by SAE to distinguish between the varying levels of autonomous capabilities. This established a hierarchical system of automation that was divided into six levels. From the SAE standard J3016: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles[10], the six levels of AVs are:

- Level 0: No automation. The human driver is required to perform all driving tasks.
- Level 1: The vehicle is primarily controlled by the human driver, but some driving assistance features are available.

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[6]McCollum, 2019; Kowall, 2013; Gooch et al., 2017; Hancock, 2017
[7]SAE, 2018; Lundberg and Lamberth, 2017
[8]Iowa, "An Act relating to Motor Vehicles," 2019
[9]SAE, 2018.
[10]SAE, 2018.

- Level 2: The vehicle has a combined set of autonomous functions such as acceleration and steering control, but the driver is still required to remain engaged on all driving tasks and must always monitor the environment.
- Level 3: The driver does not need to continuously monitor the environment but must be prepared for if the need arises in which they are required to take control in a moment’s notice.
- Level 4: The vehicle can perform all driving task with minimal limitations. The driver still has the option to take control of the vehicle, but they are not required.
- Level 5: The vehicle is capable of performing all driving functions under all conditions and without limitations. Human drivers are not required, and common vehicle features such a steering wheel, pedals, or rear-view mirrors may not be necessary.

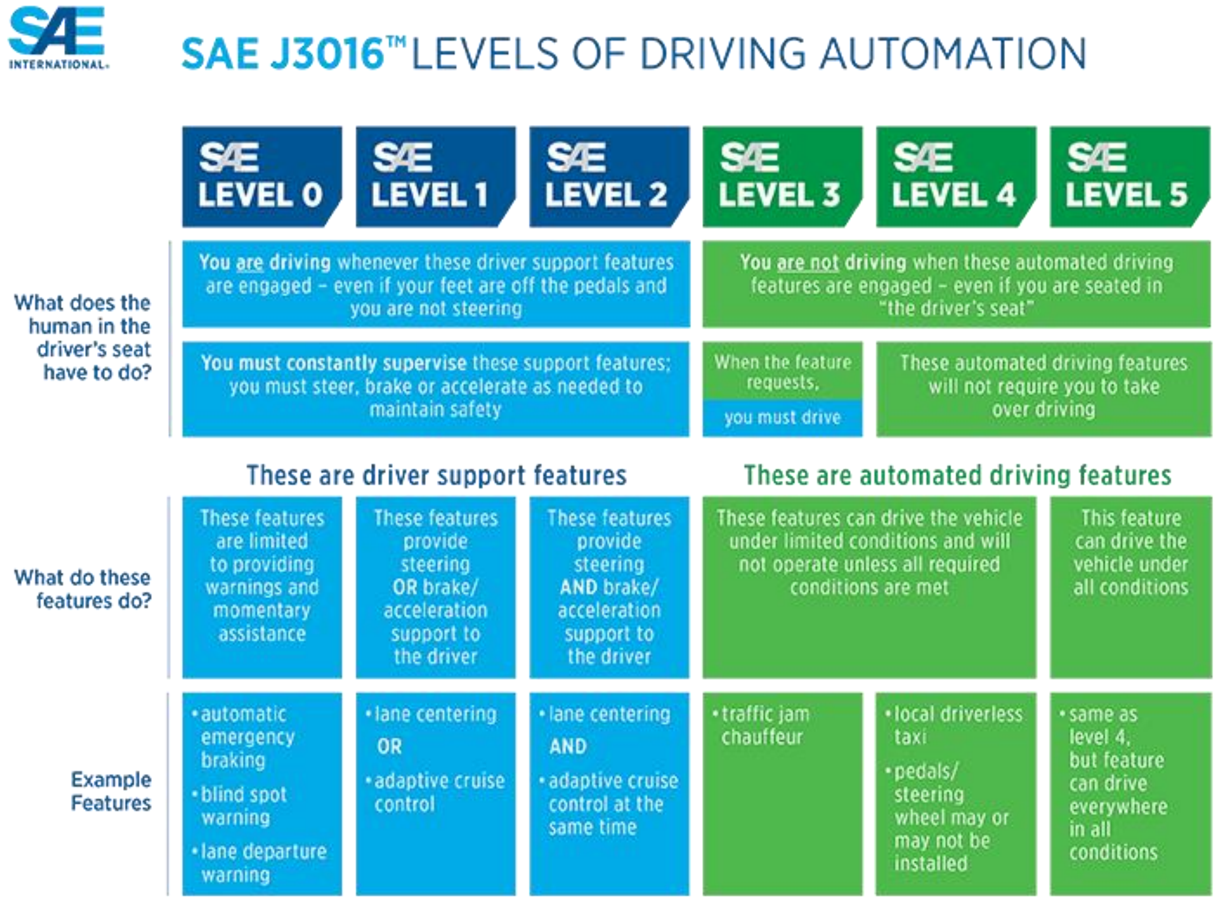

Figure 1: SAE's Definition of each level of automation[11]

AUTONOMOUS VEHICLE TECHNOLOGY

The idea of a self-driving car was made possible by the advancement of various hardware and software components that enabled its autonomous capabilities. In general, these components allow a vehicle to sense its surrounding, calculate the best desired action, and properly execute it.

Sensing is the initial task that AVs must accomplish before performing a maneuver and it is done with various sensors that are integrated into the vehicle body. This is a crucial

[11] SAE. "SAE International Release Updated Visual Chart," 2018.

part of AV technology that is used to determine a vehicle's own position and detect the behavior of all road participants within its range. Positioning can be determined by utilizing Global Navigation Satellite System (GNSS), inertial measurement units (IMU), and vehicle mileage sensors. Perception of the surrounding environment is typically obtained through lidar, radar, and/or cameras. Depending on the number of sensors that are present, once the localization and environmental perception data is obtained, a fusion strategy can be implemented. This strategy consists of all sensors simultaneously performing identification and then validating each other's results or one sensor can implement the detection of the environment while the others do the validation.[12]

Once the sensors have determined an AV's position and detected all immediate objects, a path needs to be calculated for the AV to follow. This is done by the implementation of trajectory generating and path-planning algorithms that are part of an AV's software. The entire concept of AVs depends heavily on these algorithms, and in recent years several approaches have been identified in literature.[13] Some examples include the incorporation of the Dijkstra algorithm to represent a global path, a trajectory optimization that was done while considering a vehicle in a different lane, the use of polynomial curves to plan different motion states, and the use of several Bezier curves, which were evaluated for turning motions.[14] For path planning, different methods have been investigated. That includes work from Wang et al., where a target tracking model was developed, and the global motion was studied based on the Stackelberg differential game theory.[15] In work done by Ji et al., a multi-constrained model predictive control problem

[12]Garcia et al., "Data fusion," 2012; Rodriguez et al., "Visual Confirmation," 2010.
[13]Gonzalez, "A Review of Motion Planning," 2015.
[14]Li, "Hierarchical route," 2009; Ziegler, "Trajectory Planning," 2014; Xu, "A real-time motion planner," 2012; Gonzalez, "Continuous curvature planning," 2014.
[15]Wang et al., "A Global Optimal Path Planning," 2018.

was implemented to track a planned trajectory and perform collision avoidance maneuvers.[16] Countless other path planning algorithms, such as optimal control and fuzzy logic have also been researched and shown to produce good results.[17] Although this area shows much promise, there is still more research that needs to be done, specifically in the implementation of trajectory generation and path planning algorithms designed primarily for AVs.

The final step in an AVs overall design is to execute the desired commands so that the vehicle implements the correct maneuvers and the desired motion. The trajectory tracking algorithms previously mentioned are used in AVs to provide steering, throttle, and/or braking input to control the direction and speed, as well as to guide the vehicle along a predetermined path.[18] Various controllers have been used to perform these tasks. For example, a model predictive controller (MPC) was designed to control steering by using the error between the predicted steering angle and the expected steering angle. Cost indicators were minimized, and a heuristic method was used to solve the optimization problem.[19] There are many other types of controllers that are used, such as adaptive controllers, robust controllers, or dynamic controllers. The most common controller is the Linear-quadratic regulator (LQR), which uses a linear quadratic optimization method to determine a controller gain. One example of an LQR controller was shown by Lee et al., which proposed a model-based linear-quadratic gaussian adaptive Q-matrix control method.[20] This controller was able to effectively deal with noise and error problems caused

[16]Ji et al., "Path planning and tracking," 2016.
[17]Sundar and Sharma, "Path planning for unmanned vehicles," 2019; Cao et al., "Simulation research," 2016.
[18]Katrakazas et al., "Realtime motion planning," 2015; Veres et al., "Autonomous vehicle control systems," 2011.
[19]Ollero et al., " Preditcitve Path Tracking," 1991; Ollero et al., "Control and perception," 1999; Ollero et al., "Fuzzy supervisory path tracking," 1994.
[20]Lee et al., "Optimal Path tracking." 2019

by positioning and path planning algorithms. Each of these controllers have shown promising results and they have their advantages and disadvantages when controlling AVs. With a wide array of options available to produce autonomous capabilities, more research will be needed to properly understand what would be the best control strategy that can effectively perform the desired maneuvers in self-driving vehicle. Also, these controllers are purely research-based. Therefore, they must also be applied beyond an academic setting to prove their worth in everyday driving situations.

THE ROLE OF SIMULATION

The development of AVs will require a large amount of testing in a variety of roads and driving scenarios. It would be unfeasible to attempt and run field experiments since it would be expensive, unsafe, and unlikely to produce insight on edge case scenarios. For that reason, the use of simulations is key to developing fully autonomous vehicles and enabling developers to design specific operational conditions like weather, road conditions, and traffic parameters. Simulations provide the opportunity to analyze the performance of AVs and make necessary adjustments prior to on-road testing. They also allow the rapid accumulation of valuable driving data that could not be obtained through real world driving. As a result, the amount of time spent in testing is drastically reduced, along with the cost, causing AV technology to improve at a faster rate.

There are typically three different types of simulation-based experiments that are performed on systems such as ADAS. They are Hardware-, Software-, and Driver-In-the-Loop testing. Hardware-In-the-Loop (HIL) makes it possible to repeatedly test out hardware in different scenarios. This is typically done by connecting a desired physical system and its electronic control unit (ECU) to a simulator through a network system such as CAN bus, FlexRay, or Automotive Ethernet.[21] The simulator is used to incorporate mathematical models and virtual environments that allow for the possibility of producing accurate measurements in real time. HIL has been widely used in the automotive industry and it's proven to be effective in rapidly developing hardware such as hydraulic anti-lock brake system.[22] Others have used the HIL method to improve steer-by-wire systems, specifically their effects on vehicle handling.[23] Researchers have also been able to use HIL testing to improve the algorithms of battery management systems, which are key components that monitor and control charging and discharging phases, specifically in electrically powered vehicles.[24] For research in AVs, HIL testing has also been used, such as how Gelbal used a HIL system to develop a lane-keeping controller and a cooperative adaptive cruise control application.[25] As more control systems are being completed, HIL will play an important role in the progress of ADAS.

The second type of simulation-based testing is Software-In-the-Loop (SIL), which is a method that utilizes a completely simulated environment to develop and verify preliminary software, algorithms, control systems, or any other component without the need of physical hardware. This method requires an adequate physical model of the desired system to produce an accurate analysis that is comparable to real-world testing. Gazebo, an open-source simulation tool, in combination with ROS, a framework for robotic programming, are common platforms by which simulated vehicle models are designed. For example, researchers used Gazebo and ROS to simulate the framework of an AV by modeling a Chevrolet Bolt along with a custom vehicle model and were able to produce

[21]Francisca et al., "A Systematic Review," 2019.
[22]Aly, "Hardware-in-the-Loop," 2013.
[23]Tavoosi et al., "Vehicle Handling Improvement," 2014.
[24]Morello et al., "Hardware-in-the-Loop Platform," 2018.
[25]Gelbal et al., "A Connected and Autonomous Vehicle," 2017.

accurate steering and velocity data.[26] Apart from accurate vehicle modeling, SIL is widely used primarily to validate systems and control logic. One example is how Ricardo et al. used SIL to validate a cornering braking logic they had developed.[27] They were able to use a virtual vehicle dynamics model that interfaced with a simple driver model and performed closed and open loop maneuvers. This enabled them to verify their control logic without the dangers of performing the maneuvers through on-road testing. Overall, SIL is a great way to perform tests that would be too difficult, dangerous, and/or expensive to do in a laboratory setting or on the road.

The third type of simulation-based testing in Driver-In-the-Loop (DIL), which is arguably the most crucial form of simulation-based testing, specifically for AVs. Self-driving cars will have to interact with human drivers, even when the reach Level 5 automation. For that reason, DIL is the most effective and beneficial form of simulations that can give an accurate description of the performance of all levels of AVs because it manages to incorporate the human factors. For example, DIL simulations were used to explore the safety issues that human drivers would face in a mixed traffic environment, specifically one that enabled AVs to form platoons.[28] The researchers were able to determine that traffic efficiency decreased and that human drivers had a difficulty detecting appropriate gaps for lane changing and therefore performed a more aggressive maneuver. This shows that unlike other forms of simulation-based testing, DIL can give information on how drivers behave and interact with AVs in a mixed traffic environment and the possible effects that these interactions will have on traffic safety and efficiency. For this

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[26]Syed et al., "Software-in-the-Loop Modeling," 2018.
[27]Ricardo et al., "Software-in-the-Loop development," 2007.
[28]Lee et al., "Exploring lane change safety," 2018.

reason, DIL simulation was used in this study to analyze these AV-human interactions through a safe and controlled testing environment and understand their overall effects.

Chapter 3: Design of Virtual Environments and Driving Scenarios

As was mentioned in the introduction, a key aspect of developing an ODD framework for AVs is understanding their capabilities in different roadway environments and driving scenarios. For this study, we choose to prioritize Texas roadways. Therefore, the roadway infrastructure and driving vehicles of all virtual environments were designed based on Texas regulations and design requirements. The following sections detail the design of the virtual roadways and driving scenarios that were used to test the performance of AVs with Driver-In-the-Loop simulations.

ROADWAYS

The roadway environment is a crucial part of testing the performance of AVs. Depending on the environment, there can be distinct geometric features and state regulations that an AV has to consider. To simplify our analysis, prioritization was made on analyzing AVs in a rural highway and an urban roadway environment. Specifically, the rural environment that was designed was based on a highway with an X-Configuration Interchange and the urban environment consisted of a construction area that reduced the number of lanes. Each of these environments has their own specific characteristics that were used to highlight the performance of AVs in different circumstances. The geometric configuration used for each environment was based on the Texas Department of Transportation (TxDOT) Roadway Design Manual.

Highway: X-Configuration

Although Texas has a large number of roads, the majority are part of a highway system. Therefore, the X-Configuration of the structures that was prioritized in order to gain insight about how its geometric features, traffic characteristics, and driving behaviors impact different levels of AVs on this type of environment. The highway environment was designed as a 15-mile-long, six lanes divided, controlled-access freeway that consists of ten equally spaced interchanges with one-way frontage roads on each side. The environment consists of typical characteristics that are found in Texas highways. That includes typical signage such as speed limit, entrance/exit ramp, interstate, and stop signs. Common lane markings were implemented in the environment and adhere to TxDOT's Roadway Design Manual.[29] The geometric configuration consists of an at-grade facility that slopes upward as it approaches an interchange and produces an overpass, allowing the frontage roads on each side to connected. After passing the interchange the highway returns to grade. This geometric configuration is continuously repeated for each interchange.

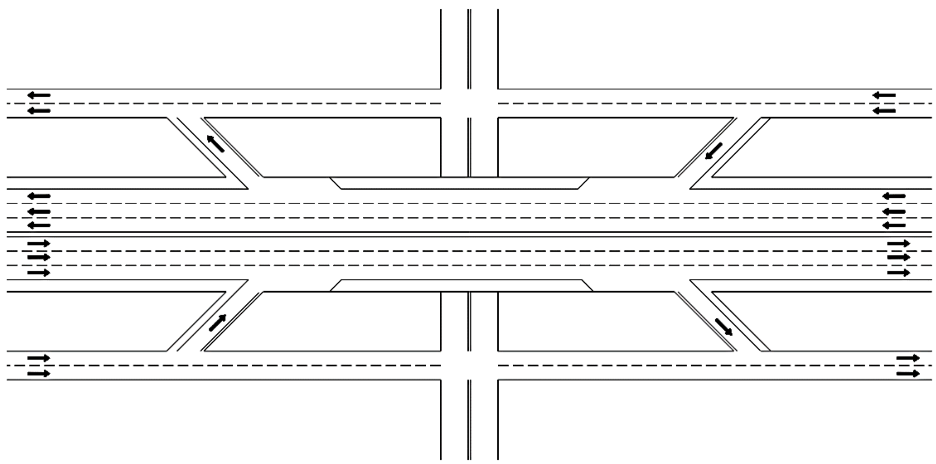

Figure 2: X-Configuration Interchange

The highway environment contains an X-Configuration Interchange, seen above in Figure 2, which serves as the foundational structure for this virtual environment. An X-Configuration, also known as a Reverse diamond, is a specific configuration of the Diamond Interchange, which is one of major designs used in Texas. The X-Configuration

[29]TxDOT Roadway Design Manual.

Interchange connects a frontage road with the highway by means of an on-ramp that tapers into the main lanes. This type of pattern is primarily used in locations with significant traffic movement along frontage roads and manages to provide access between interchanges, preventing exiting queues from backing up onto the freeway. Each interchange is separated by approximately 1.5 miles, and successive ramps are separated by approximately 2,250 feet. As mentioned before, the design of this roadway follows the guidelines from the TxDOT Roadway Design Manual. A summary of the quantitative measurements for the roadway geometry is shown in Table 1 and an overview of the developed virtual road is shown in Figure 3. More figures of the entire track are in the Appendix.

	Parameters	**Value**
Highway	Total Length	15 miles
	# of Interchanges	10
	# of Lanes	3
	Lane Width	12 ft
	Median Distance	10 ft
Frontage Roads	Total Length	15 miles
	# of Intersection	3
	# of Lanes	2
	Lane Width	12 ft
Ramps	Angle of Intersection	3 Degrees
	Horizontal Length	885 ft
	Vertical length	45 ft
	Entrance Acceleration length	577 ft
	Entrance Taper length	301 ft
	Exit Deceleration Length	344 ft
	Exit tape length	301 ft
Overpass	Clearance	17 ft
	Maximum Height	23.6 ft
	Grade	3 %

Table 1: Highway Geometric Measurements developed in virtual reality.

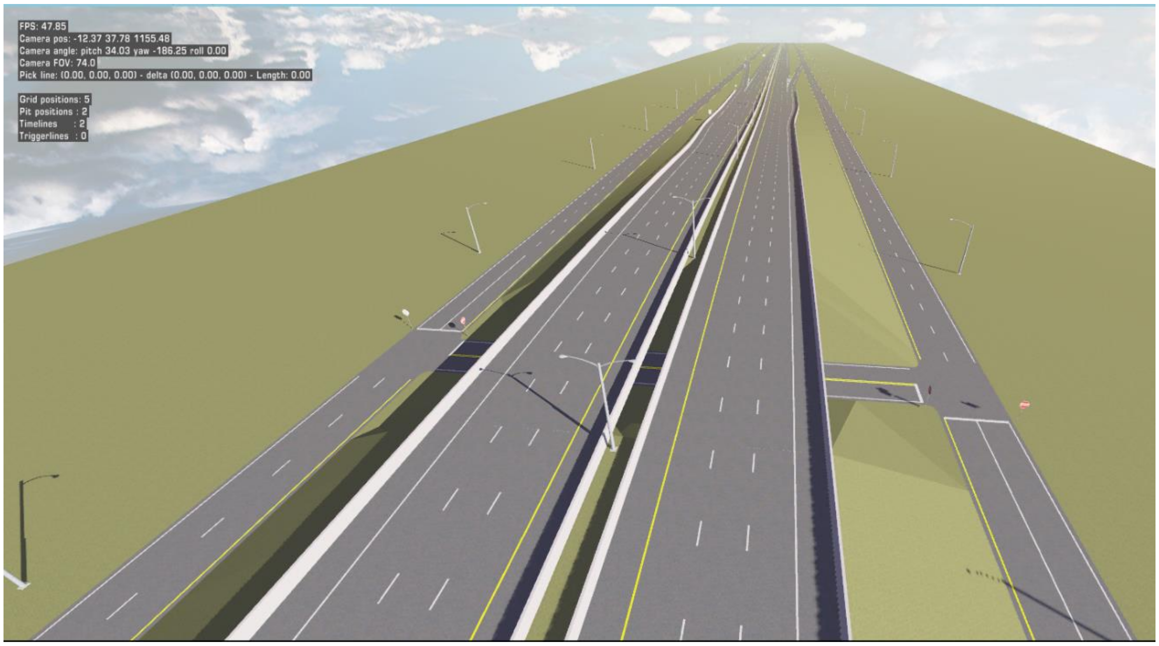

Figure 3: Ariel view of Highway Interchange Section.

Urban: Construction Lane Drop (Special Case)

The urban environment was selected to gain insight into the impacts that a complex roadway would have on the performance of AVs. Overall, this urban environment was designed as a six-block network that was surrounded by a circulating road and evenly divided by three intersecting roads. It also consists of common characteristics found in urban cities such as intersections, construction zones, parallel parking, bus stops, and sidewalks. The roads in this environment vary between a two or four lane undivided facility and contain structures that are synonymous with urban cities. It must be noted that a true analysis in an urban environment would contain interactions between vehicles, pedestrians and/or cyclists but for this study those factors were excluded. Instead, the focus of this study was primarily on simulating and analyzing vehicle-to-vehicle interactions.

Within this environment there were six distinct structures that pertain to urban roadways. They were a Bus Dwell area, a Right Turn Only Lane, on-street parallel parking, a Mid-block Driveway, a Transit Bus halted at a bus stop, and a construction zone area. For this study, the focus was only on the construction zone lane drop. Therefore, the description of all other structures will be excluded from this thesis, but are shown through various figures in the Appendix. The construction zone was located in the outside right lane of a 4-lane undivided road. This was made to produce a lane drop that would force all vehicles to merge into the available inner left lane. The construction zone has a total length of 413 feet that is subdivided into the merging taper, buffer space, construction area, and downstream taper. The length of each subsection is 180 feet, 85 feet, 50 feet, and 98 feet, respectively. Preceding the construction zone are three signs that indicate advanced warnings to drivers of upcoming road work and directs them to begin merging to the left lane. The signs are separated by a length of 120 feet. Since this structure was the focus out of the entire urban environment, a specific route was designed within the roadway that would guide drivers and all simulated traffic in such way that they only encountered the construction zone lane drop and no other structure. This was done by closing off additional roads with construction barrels. The resulting closed route consisted of a straight path with three intersections, followed by a semicircular section in which the construction zone was located. The total length of the route was 2295 feet. The developed visual representation of the urban roadway, along with an outline of the desired route is shown below in Figures 4 and 5. A full visual description of all sections in the urban environment are shown in the Appendix.

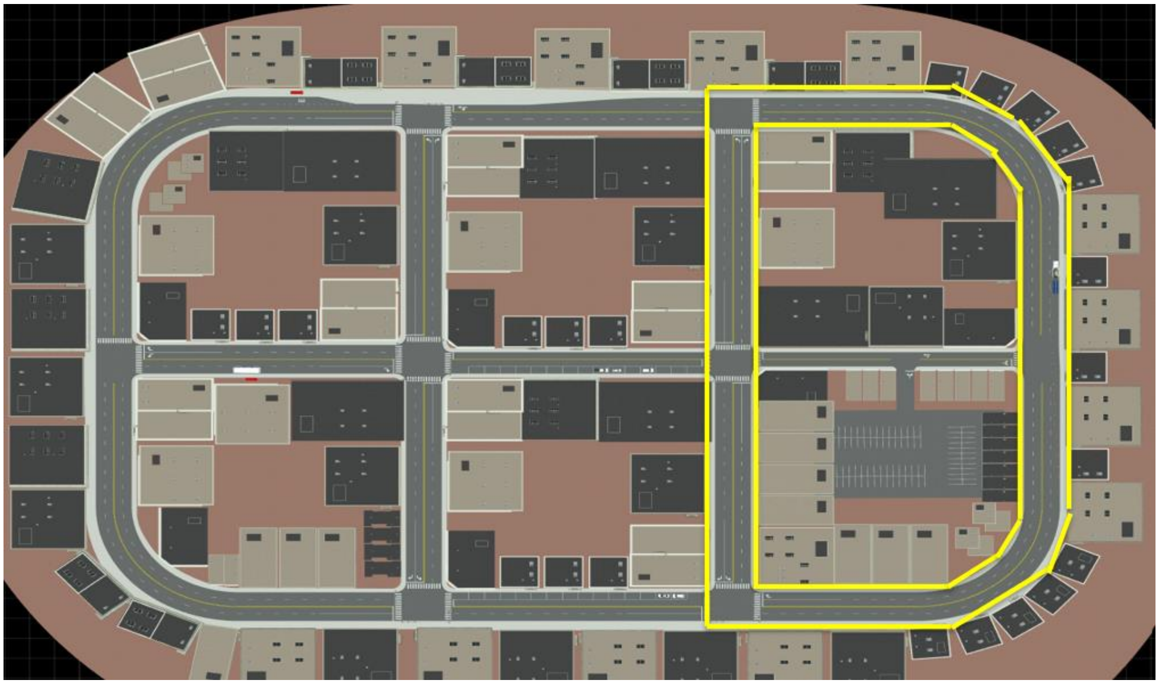

Figure 4: Urban Track and the designated route (yellow outline).

Figure 5: Designated route of the Urban Roadway.

DRIVING SCENARIOS

Other than the roadway environment, an AV must perform well under different driving situation. The two primary scenarios chosen for this study were a forced lane change maneuver, in which a driver is forced to merge due to a lane drop, and a merging vehicle scenario, where a traffic vehicle inserts itself into the direct path of the driver. Within each environment a Level of Service (LOS), defined as the number of vehicles per lane, was applied to the traffic. More specifically, LOS A and D were used to define the density of traffic for both environments. For a highway environment, LOS A is considered free flow traffic with an average headway distance between vehicles of about 480 ft (146 m), and LOS D is considered congested with an average headway of 150 ft (46 m) between each vehicle. For both definition of LOS, the speed of traffic would remain a constant value of 65 mph (105 km/h). For urban roads, LOS A was defined as traffic with an average headway of about 200 ft (61 m) and a speed of about 25 mph (40.2 km/h). LOS D was defined with an average headway of about 35 ft (11 m) and a speed of about 7 mph (11.2 km/h). The following sections will describe the two driving scenarios as they pertain to either the highway or urban environment and will detail how the traffic vehicles were programmed.

Highway: Force Lane Change

The Highway Forced Merge Maneuver focused on how an ADS might perform when being forced to merge into the highway main lanes as it is entering via an on-ramp. In this scenario there were 12 surrounding vehicles continuously traveling on the main lanes with 5 vehicles located in the right-most lane, 4 vehicles in the center lane, and 3 vehicles in the left-most lane. They were designed to maintain headways classified as LOS A during the first five interchanges and transition to a LOS D for the remaining five interchanges. All vehicles traveled at a speed of 65 mph (105 km/h), excluding the LOS A to D transition segment between Interchanges 5 and 6, which required the vehicles to accelerate and decelerate. Two vehicles were located in the frontage road alongside the subject vehicle, with one being placed in front, used as a guiding vehicle, and the other behind it. The guiding vehicle was programmed to continuously enter and exit the highway at each interchange. All traffic used this vehicle as a reference when performing any required acceleration or deceleration in the simulation. The guiding vehicle also maintained a constant speed of 50 mph (80 km/h) when traveling along the frontage road and increased its speed to 65 mph (105 km/h) upon entering the main lanes. The vehicles traveling in the main lanes all maintained a speed of 65 mph (105 km/h) when the guiding vehicle entered the highway but would otherwise vary their speed to assure that they were always present when the guiding vehicle entered through the on-ramp. Each vehicle had a level of automation assigned to it based on the test that was being performed and will be describe later in the experimental setup. Figure 6 gives a visual representation of the traffic structure. In the figure, A2–A7 and Driver (Blue) represent vehicles that were programmed with a full vehicle dynamics model. D1-D8 (Red) represent “dummy” vehicles, that are predefined objects without a dynamic model, which prevents them from interacting or being influenced by the environment.

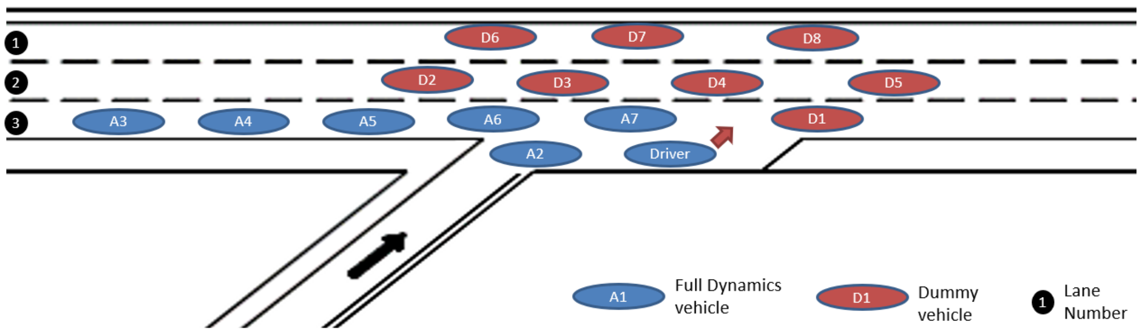

Figure 6: Diagram of Highway Forced Lane Change. A2–A7 and Driver (Blue) contain full vehicle dynamic models. D1–D8 are "dummy" vehicles, void of dynamic models.

Highway: Merging Vehicle – On-Ramp

This driving scenario focused on how ADS would perform during the event in which another vehicle entered the highway through an on-ramp. In this scenario there were 13 surrounding vehicles on the main lanes. Four vehicles in the left-most lane, four vehicles in the center lane, and five vehicles were traveling in the same lane as the subject vehicle, with two in front and three behind it. Initially, a separate traffic vehicle was placed on the frontage road to continuously enter and exit the highway through the interchange on/off ramps and perform the merging maneuver to which the highway vehicles would be responding to. The 12 surrounding vehicles alongside the human subject were separated by about 480 ft (146 m), classified as LOS A, during the first five interchanges and transitioned to about 150 ft (46 m), classified as LOS D, for the remaining five interchanges. All traffic vehicles traveled at a speed of 65 mph (105 km/h) except during the transition between LOS A to D, which required the vehicles to accelerate and decelerate to achieve the required headways. The vehicle initially located on the frontage road was also excluded from the 65-mph speed parameter, varying its speed as necessary to accurately perform the merging maneuver at each interchange. The vehicle in front of the subject vehicle was designated as the guiding vehicle. The traffic used this vehicle as a reference when performing any required acceleration or deceleration. The guiding vehicle also maintained a constant speed of 65 mph (105 km/h) throughout the entire length of the track. Each vehicle was assigned a level of automation based on the test that was being performed. Figure 7 provides a visual representation of the traffic structure, where A2–A7 and Driver (Blue) represent vehicles that are programmed with a full vehicle dynamics model and D1–D8 (Red) vehicles represent "dummy" vehicles, which did not have a dynamic model to produce data.

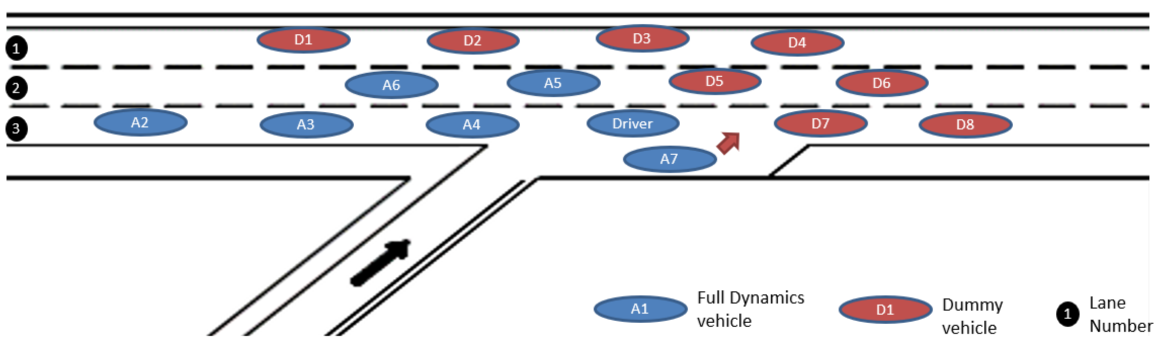

Figure 7: Diagram of Highway Merging Vehicle – On-Ramp. A2–A6 and Driver (Blue) contain full vehicle dynamic models. D1–D8 are "dummy" vehicles, void of dynamic models.

Urban: Forced Lane Change

The Urban Forced Lane Change scenario focused on how an ADS would perform as it is forced to merge into an adjacent lane due to a construction lane drop. For this situation there were seven vehicles traveling alongside the subject vehicle and seven others designated as oncoming traffic. Traffic vehicles were designed to maintain a distance and speed based on arterial LOS from the Highway Capacity Manual.[30] For the first five laps the traffic vehicles maintained an arterial LOS A, which consists of a speed of about 25 mph (40.2 km/h) and a distance between vehicles of about 200 ft (61 m) Then, an arterial LOS D was maintained for the remaining five laps, which consists of a speed of about 7 mph (11.2 km/h) and a distance between vehicles of about 35 ft (11 m). There were two vehicles traveling in the right lane along with the subject vehicle. One in the front of the vehicle, which was designated as the guiding vehicle, and the other was behind it. The remaining four vehicles traveling along the same direction were placed in the left lane. The guiding vehicle was programmed to initially start at an intersection and follow the right lane, properly merging into the left lane when approaching the construction lane drop. It was then programmed to return to the right lane after passing the construction zone. The guiding vehicle was designed to drive for 10 laps around the designated route before stopping at the initial intersection and completing the experiment. The oncoming traffic remained constant throughout the entire track to assure that they would be present when the human driver traveled through the construction lane drop. Figure 8 presents a visual representation of the proposed traffic structure, where A2–A7 and Driver (Blue) represent vehicles that are programmed with full vehicle dynamics model, which will produce the data output, and D1–D8 (Red) were “dummy” vehicles, which were void of the vehicle dynamics model and did not produce output.

[30] Highway Capacity Manual

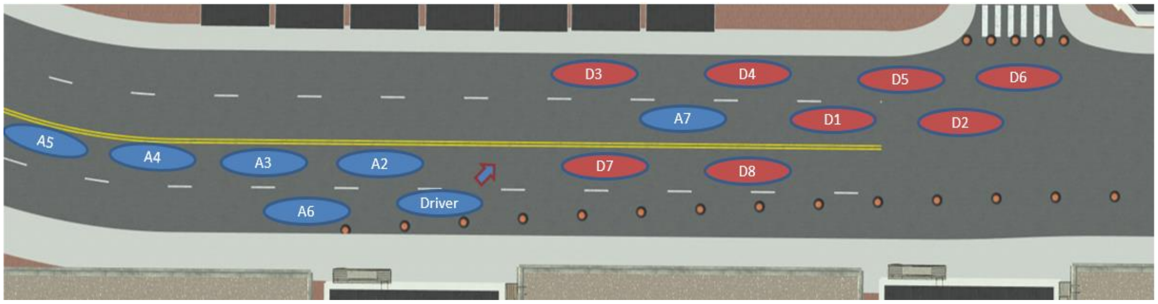

Figure 8: Diagram of Urban Forced Lane Change. A2–A7 and Driver (Blue) contain full vehicle dynamic models. D1–D8 are “dummy” vehicles, void of dynamic models.

Chapter 4: Vehicle Modeling and Simulation

The development of ADAS is dependent on modeling and simulations. Before a controller can be designed, an accurate physical model of the system needs to be established to produce the correct dynamic behavior. This is especially significant with motion-base simulator, which requires correct dynamic models to produce a realistic driving feel. The following sections will give details into the vehicle models used to develop accurate dynamic motion for the traffic vehicles and the human driver. Also, a description of the driving simulator will be given, detailing how the features that it possesses allow for a realistic driving experience.

DYNAMIC VEHICLE MODEL

The models used to describe a dynamic system are crucial to developing control algorithms. When it comes to dynamic vehicle models, various iterations have been proposed and implemented to design many controllers that are used to control throttle, brake, and steering. For our study, an important factor to consider was the accuracy of the driving experience, which needed to be as close to reality to produce comparable data. For this reason, we implemented the industry leading Automotive Simulation Models (ASM), provided by dSPACE, in combination with our six degrees-of-freedom (dof) driving simulator. ASM provides simulation models for various automotive applications that can be combined as needed. It includes proven Simulink models of individual components such as combustion engines, electric motors, vehicle dynamic systems, and complex traffic scenarios. These models have been used throughout the industry for model-based function development, given that its components can work in conjunction to produce realistic vehicle dynamics and motion.

The most crucial model for our study was ASM's Vehicle Dynamics Model, which was designed by dSPACE as a multibody passenger car.[31] Its components include a drivetrain with elastic shafts, a table-based engine, two semi-empirical tire models, a nonlinear table-based vehicle suspension model with kinematics and compliance, a steering model, and aerodynamics. The model considers six dof for vehicle motion, four dof for wheel relative motion, one dof for steering, and four dof for wheel rotation. A diagram of the ASM Vehicle Dynamic Model can be seen in Figure 10.

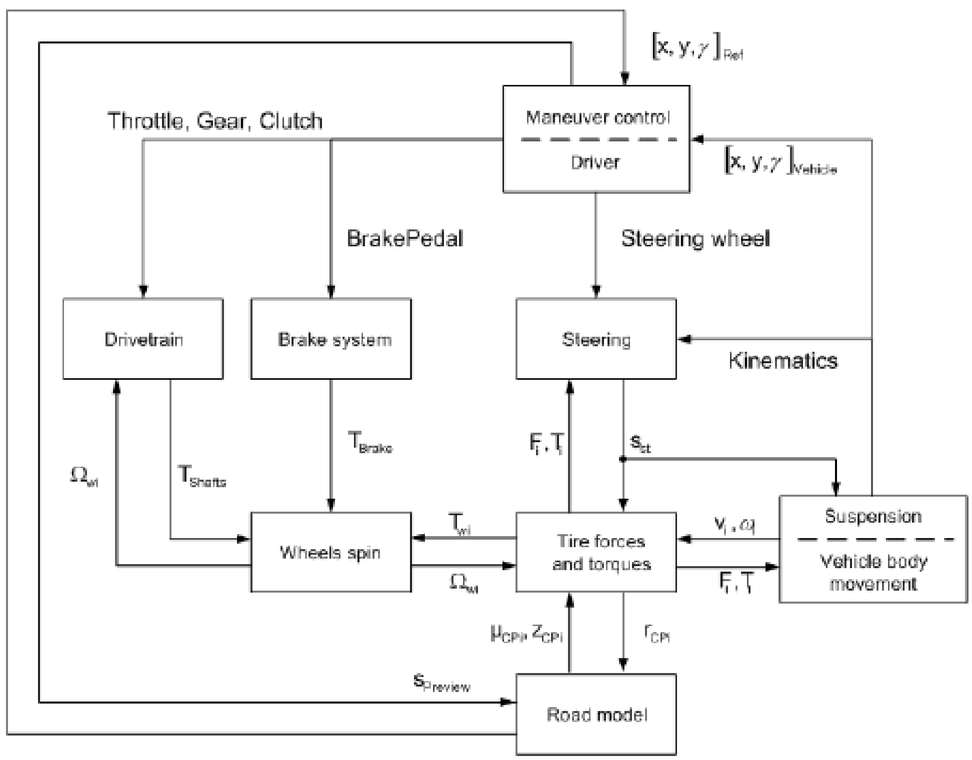

Figure 10: Diagram of the ASM Vehicle Dynamic Model.[32]

[31] ASM Vehicle Dynamics

[32] ASM Vehicle Dynamics

Before describing the vehicle dynamic model used by ASM, the coordinate systems that are used as the basis for its model should be explained. To start, ASM uses a system of several coordinate systems, shown in Figure 11, all rotating clockwise. In the figure, the earth coordinate system, index E, represents the fixed reference. The Vehicle reference, index V, is fixed to the vehicle body and its origin is at the midpoint of its front wheels with the x-axis being its longitudinal direction and the y-axis being its lateral direction. The wheel coordinate system, indexed W, is at the center of the wheel and its orientation is determined by the wheel orientation, which depends on suspension kinematics of the model. Finally, the contact point (CP) coordinate system has its origin in the wheel's CP and the x-y plane is parallel to the road.

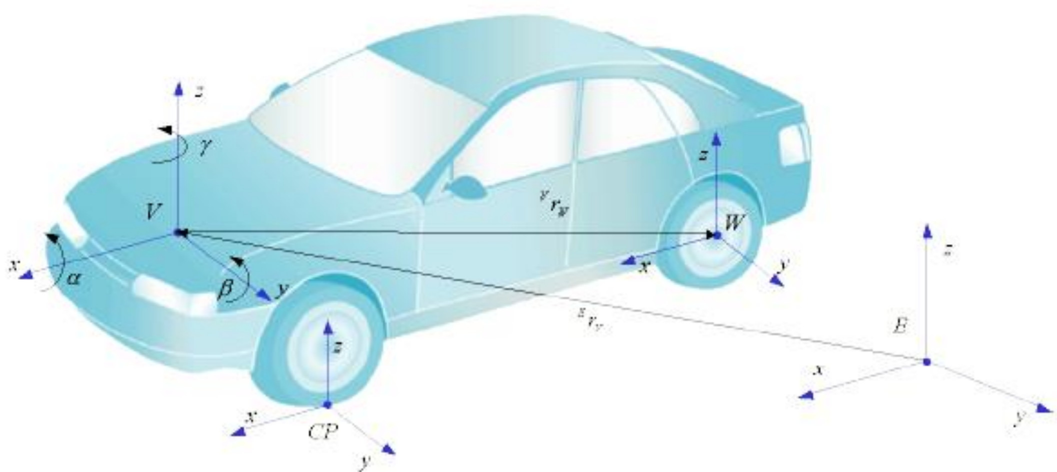

Figure 11: ASM Vehicle Coordinate Systems.[33]

As previously mentioned, ASM implements a multibody system technique to solve the equation of motions for each degree of freedom and calculate the velocities and position of the vehicle and its wheels. The equation of motions can be written as:

[33] ASM Vehicle Dynamics.

$$M\ddot{q} = Q$$

where M is a generalized 10x10 mass matrix, q is a 10x1 generalized degrees of freedom vector, and Q is a 10x1 generalized forces and torque vector. The generalized degrees of freedom are as follows:

$$\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix}_v , \qquad \begin{bmatrix} \dot{q}_4 \\ \dot{q}_5 \\ \dot{q}_6 \end{bmatrix} = \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix}_v , \qquad \begin{bmatrix} \dot{q}_{FL} \\ \dot{q}_{FR} \\ \dot{q}_{RL} \\ \dot{q}_{RR} \end{bmatrix} = \begin{bmatrix} \dot{z}_{FL} \\ \dot{z}_{FR} \\ \dot{z}_{RL} \\ \dot{z}_{RR} \end{bmatrix}$$

These consist of the translational vehicle velocities of the origin of the vehicle coordinate system, the angular vehicle velocities about the x, y, and z-axes of the vehicle coordinate system, and the vertical speed of the wheels with respect to the vehicle coordinate system. The mass matrix is a function of wheel position and kinematic suspension; therefore, it is not constant, as it is calculated at every simulation step. The velocities of the vehicle and wheels are calculated according to the generalized degrees of freedom, position of center of gravity (CoG), and the wheels' relative velocities. The velocities for the vehicle's CoG are calculated as follows:

$$v_{CoG} = v_V + \omega_V \times r_{CoG}$$

$$\omega_{CoG} = \omega_V$$

and for the wheel center, the velocities are calculated by,

$$v_{Wi} = v_V + \omega_V \times r_{Wi} + \dot{r}_{Wi}$$

$$\omega_{Wi} = \omega_V + \omega_{Wi\_rel}$$

where i represents Front Left (FL), Front Right (FR), Rear Left (RL), or Rear Right (RR), r_{Wi} is the wheel position represented in the vehicle system, $\dot{r}_{Wi}$ is the wheel velocity relative to the vehicle, and ω_{Wi_rel} is the wheel angular velocity relative to the vehicle.

Each degree of freedom also has a corresponding force or torque, and they are calculated by tire, aerodynamics, mass forces and torques, and suspension forces in the direction of the relevant degree of freedom. The mass forces and torques depend on residual acceleration, gravity acceleration, and angular velocity. To obtain the residual acceleration you start with the expression for acceleration of any given wheel:

$$a_{Wi} = \dot{v}_V + (\dot{\omega}_V \times r_{Wi}) + [\omega_V \times (v_{Wi} + \dot{r}_{Wi})]$$

where v_V is vehicle velocity, ω_V is vehicular angular velocity, v_{Wi} is absolute wheel velocity, r_{Wi} is the wheel position vector. The residual acceleration would be the third term,

$$a_{RWi} = \omega_V \times (v_{Wi} + \dot{r}_{Wi})$$

With this residual acceleration, the mass force can be calculated as,

$$F_{RWi} = -m_{Wi} * a_{RWi}$$

and to obtain the total mass force for a wheel, the mass force due to residual acceleration and gravity force are summed as follows:

$$F_{mWi} = F_{RWi} + m_{Wi} * g$$

As for the mass torque, the expression used by ASM is:

$$T_{mWi} = -[J_{Wi}\alpha_{Wi} + \omega_{Wi} \times J_{Wi}\omega_{Wi} + \omega_{Wi} \times \Theta\Omega e_{Wi}]$$

were,

α_{Wi} is wheel residual acceleration

ω_{Wi} is absolute wheel angular velocity

Ω is wheel rotational speed about its axis

e_{Wi} is the wheel position vector

Θ is inertia about the wheel rotational axis

J_{Wi} is the inertia tensor of the wheel

As was previously mentioned, these mass forces and toques are used in combination with external forces such as tire, aerodynamics, and suspension to calculate the overall generalized forces and torques of dSPACE's ASM Vehicle Dynamic Model.

DRIVING SIMULATOR

Simulations are useful for analyzing AVs, especially when validating controllers before they are implemented in on-road testing. Simulation-based research has also been used to analyze how different scenarios involving AVs affect traffic safety and efficiency. Still, these types of simulation have to use driver models to represent human behavior and lack a true representation of AV-human interaction. For that reason, it is necessary to incorporate actual human subjects that can interact with ADAS functionality to better understand how these interactions will affect traffic safety and efficiency. This makes the use of a motion-base driving simulator a necessity when developing these systems because they can provide realistic vehicle dynamic motions, human responses, and traffic interactions that would be expected in real traffic.

The driving simulator that we used to test the performance of ADAS in mixed traffic, shown in Figure 12, has professional driver interface equipment, such a seat, pedals, and a steering wheel. It consists of a six-degree-of-freedom hexapod that uses stroke actuators to provide longitudinal, lateral, and vertical movement and yaw, pitch, and roll rotations. The system can also provide force feedback through the steering wheel by using a control loading motor to produce continuous torque. Auditory feedback (e.g., engine sound, tire friction, etc.) is also incorporated in the simulator by four surrounding speakers and one sound engine that lays below the simulator. This combination of the motion, haptic, and auditory feedback work simultaneously in an accurate and fast manner to establish a realistic driving experience for the human subjects.

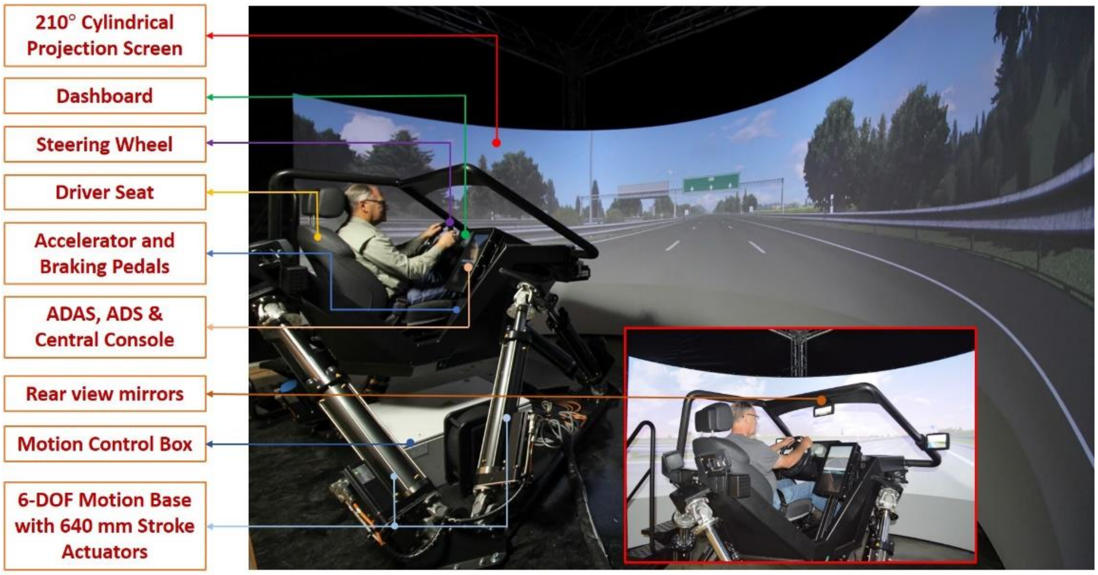

Figure 12: Six degree-of-freedom motion-based driving simulator

Apart from the driving platform, the visual representation of the desired virtual environment is produced by three projectors that display the graphics on a 210-degree conical screen. The conical screen gives the driver a perception of being immersed in the virtual environment. All three projectors are synchronized to be updated in real time to maintain a small latency and establish a smooth transition between frames, decreasing the possibility that a human subject experiences a mismatch between graphics and motion.

Chapter 5: Design of ADAS Controllers

By using ASM, it was also possible to integrate controllers into the systems without having to redesign the vehicle model. Although this was possible, for this study it was decided to limit the implementation of new controllers. This was done to ensure that the performance analysis of AVs would be on well-established ADAS controllers that will most likely be deployed in the immediate future, and therefore be part of the mixed traffic scenario. For that reason, the control systems implemented by dSPACE's ASM were primarily used for this study, with a few exceptions, which were control systems that needed to be designed to incorporate the interface equipment of the driving simulator. In this chapter the ADAS controllers used to define each level of automation will be described in the following sections.

Lane Departure Warning (LDW)

As was previously defined in Chapter 2, Level 0 is described as having no automation and requiring the human driver to perform all driving tasks. Still, some minor assistance from the vehicle can be incorporated, such as emergency or warning systems. One such warning system that was implemented with the driving simulator was Lane Departure Warning (LDW). This was a simple control system that calculated the distance to the lane's edge and a predetermined threshold value of 1.1 meters was used to determine a deviation from the center of the lane. If the vehicle unintentionally deviated from its respective lane and its distance to the lane's edge went below the given threshold value, the simulator interface would display a visual alert in the dashboard. The Simulink block diagram of the control system is shown in Figure 13.

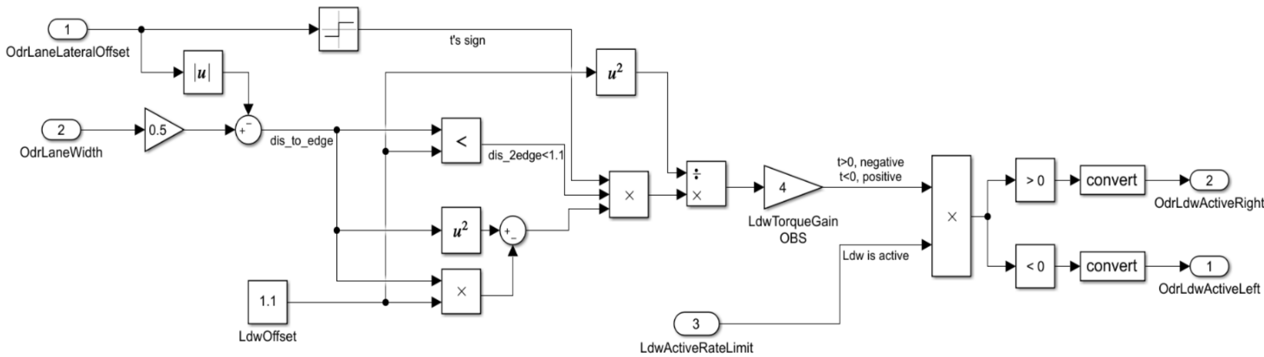

Figure 13: Simulink Block Diagram of the Lane Departure Warning

LONGITUDINAL CONTROL

Level 1 AVs are defined as providing either lateral or longitudinal control. For our study we implemented longitudinal control, as it is the most common feature of level 1 AVs that will be entering the market. For our longitudinal controller we incorporated Adaptive Cruise Control (ACC), which assists drivers in the acceleration and braking. Two distinct ACC systems were implemented, one for the ego vehicle, which would be driven by the human subject and incorporate the driving simulator interface. The other ACC system would be implemented to the virtual traffic vehicles that were simulated by dSPACE's ASM software. Regardless of the difference, both ACC systems used a double feedback-loop structure, where headway and velocity are tracked, then varied with respect to a desired distance by Proportional-Integral (PI) controllers.

The ACC system for dSPACE is outlined below in Figure 14. As shown, the desired distance from a target vehicle is calculated from a distance time set, the actual velocity, and the current distance. This value is used by the PI distance controller to adjust the vehicles' reference velocity. This value is then compared to the current velocity to obtain an error that is used by a PI velocity controller that calculates a desired longitudinal acceleration. To avoid a rapid change in the desired acceleration, a rate limiter is applied into the ACC system. Also, an Automatic Emergency Braking (AEB) system is incorporated to brake the vehicle if the distance to the target vehicle decreases rapidly.

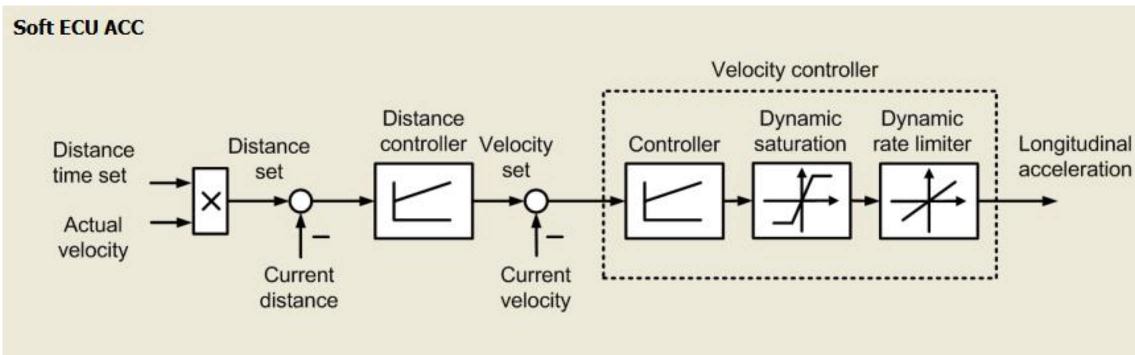

Figure 14: dSPACE's Adaptive Cruise Control system.[34]

As was mentioned, a separate ACC system was implemented for the ego-vehicle to incorporate the simulator's interface, which includes steering wheel switches that allow the human drivers to activate the ACC and set a desired speed and distance. Similar to dSPACE's ACC, the ego vehicle's control system takes the desired values along with the actual distance and speed from a target vehicle and implements two PI controllers to calculate the desired acceleration. The only difference that ego-vehicles ACC system possesses is that it allows the human driver to disable the systems by stepping on the throttle or brake pedal. The Simulink block diagram for the ego-vehicle's ACC is shown below in Figure 15.

[34] ASM Environment.

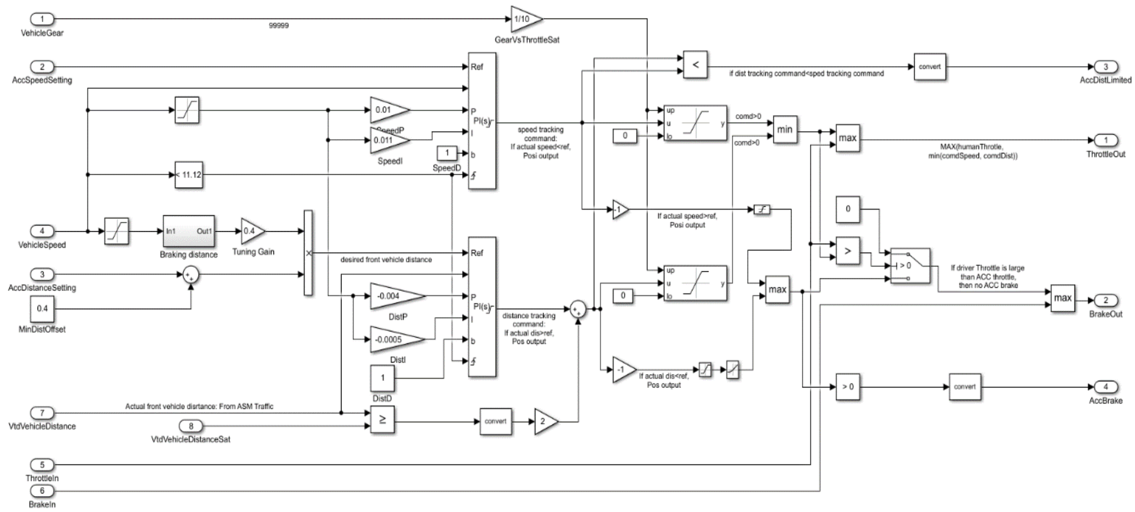

Figure 15: Ego Vehicle Adaptive Cruise Control

LATERAL CONTROL

For level 2 AVs a lateral control is incorporated to maintain the vehicle inside of a desired lane. For all the traffic vehicles, including the ego-vehicle, the same lateral controller from dSPACE was implemented. This controller is based on the state space format of the reduced bicycle model, which is shown in Figure 16. For the bicycle model, it is assumed that the tire forces are linear and can be represented by the following equations:

$$F_{y,wheel,front} = 2C_F \alpha_{wheel,front}$$

$$F_{y,wheel,rear} = 2C_R \alpha_{wheel,rear}$$

where

$$\alpha_{wheel,front} = \delta_{steering} - \arctan\left(\frac{v_{y,vehicle} + a\dot{\gamma}_{vehicle}}{v_{x,vehicle}}\right)$$

$$\alpha_{wheel,rear} = \arctan\left(\frac{v_{y,vehicle} + b\dot{\gamma}_{vehicle}}{v_{x,vehicle}}\right)$$

C_F is the cornering stiffness of the front wheels

C_R is the cornering stiffness of the rear wheels

The bicycle mode can then be represented as,

$$m_{vehicle}\dot{v}_{y,vehicle}$$
$$= F_{y,wheel,front}\cos(\delta_{steering}) + F_{y,wheel,rear}$$
$$- v_{x,vehicle}\,\dot{\gamma}_{vehicle} m_{vehicle}$$

$$J_{vehicle}\ddot{\gamma}_{y,vehicle} = aF_{y,wheel,front}\cos(\delta_{steering}) - bF_{y,wheel,rear}$$

These equations are then restructured into the state space format:

$$\dot{x} = \begin{bmatrix} 0 & 1 & 0 & v_{x,vehicle} \\ 0 & \dfrac{-2(C_F + C_R)}{m_{vehicle}v_{x,vehicle}} & \dfrac{2(bC_R - aC_F)}{m_{vehicle}v_{x,vehicle}} - v_{x,vehicle} & 0 \\ 0 & \dfrac{2(bC_F - aC_R)}{J_{vehicle}v_{x,vehicle}} & -\dfrac{2(a^2C_F + b^2C_R)}{J_{vehicle}v_{x,vehicle}} & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ \dfrac{2C_F}{m_{vehicle}} \\ \dfrac{2aC_F}{J_{vehicle}} \\ 0 \end{bmatrix} \delta_{steering}$$

$$y = [1 \quad 0 \quad 0 \quad 0]x$$

where the state vector and output signal are respectively,

$$x = [Pos_{y,vehicle} \quad v_{y,vehicle} \quad \dot{\gamma}_{vehicle} \quad \gamma_{vehicle}]$$
$$y = Pos_{y,vehicle}$$

For the control law, the solution of the linear system is given as

$$y(kT) = C\Phi(kT)\,x(0) + C\Gamma(kT)B\,u(0)$$

where kT is a discrete time point and

$$\Phi(kT) = e^{AkT}$$
$$\Gamma(kT) = \int_0^{kT} \Phi(\tau)d\tau$$

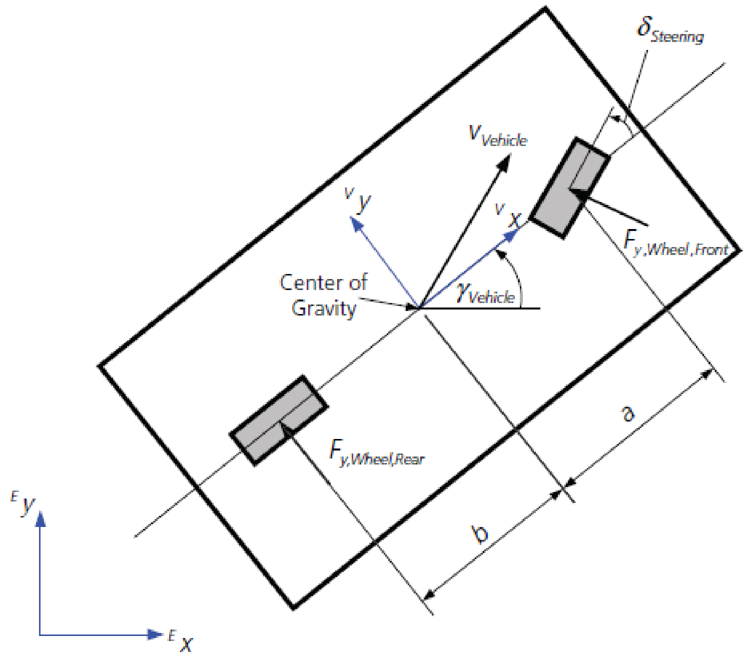

Figure 16: Bicycle Model.

The lateral controller functions by attempting to minimize the following objective function,

$$J = \sum \left(y_{ref}(kT) - y(kT) \right)^2 W_k$$

which is the weighted difference between the reference and output signal summed over a number of preview points. By inserting the linear solution into the objective function, you obtain the following,

$$J = \sum \left(y_{ref}(kT) - C\Phi(kT)\, x(0) - C\Gamma(kT)Bu(0) \right)^2 W_k$$

Then, by taking the derivative of J with respect to $u(0)$ the control law can be calculated in the following closed form,

$$u(0) = \frac{\sum(y_{ref}(kT) - C\Phi(kT)x(0)(C\Gamma(kT)BW_k)}{\sum((C\Gamma(kT)B)^2 W_k)}$$

The reference position is equal to the y coordinate value of the vehicle, obtained from a road subsystem, and $u(0)$ is equaled to the steering angle, therefore the final equation for the lateral controller is,

$$\delta_{steering} = \frac{\sum(Pos_{y,Road} - C\Phi(kT)x(0)(C\Gamma(kT)BW_k)}{\sum((C\Gamma(kT)B)^2 W_k)}$$

As has been described, the lateral controller is based on optimal control theory and manages to keep the vehicle on the road by controlling the steering wheel. This resulting angle is then provided as a signal to the vehicle. A main signal flow of the lateral control subsystem used in dSPACE, along with its connection to the road and vehicle mode, is shown below in Figure 17.

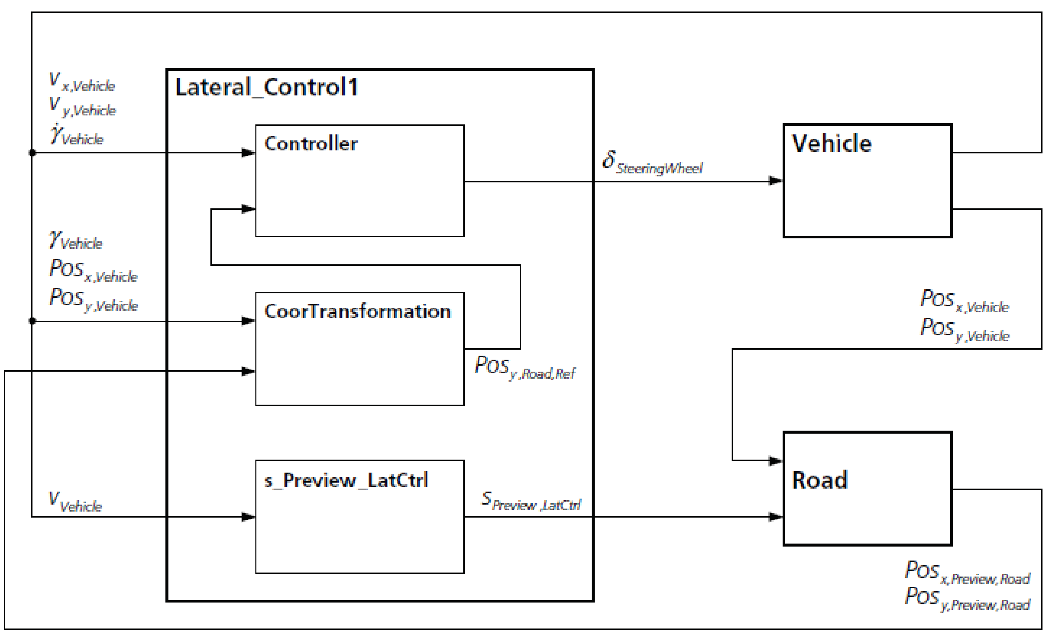

Figure 17: Diagram of Lateral Control signal flow.[35]

[35] ASM Environment.

Chapter 6: Preliminary Driver-In-the-Loop Experiments

The following chapter describes the preliminary DIL experiments that were conducted for both the highway and urban environment. These experiments were meant to verify the practicality of the virtual environments, with the goal of establishing a framework that can be used for future human subject studies. A description of the metrics used to analyze the performance of the vehicles is also given, and the results obtained from the Driver-In-the-Loop simulations are presented and discussed. The preliminary DIL experiments, which involved human participants, were approved by UT Institutional Review Board (IRB) under the protocol number 2018080099-MODCR02.

EXPERIMENTAL SETUP

As was discussed in Chapter 1, the two scenarios that were used for analyzing AV performance were the Forced Lane Change and the Merging Vehicle. These two scenarios are some of the most problematic events that an AV can encounter. For that reason, it was decided to analyze the performance of AVs based on these scenarios for both the highway and urban roadway. The experiments were divided into each driving scenario previously described in chapter 3, which were the Highway Forced Lane Change, the On-ramp Merging Vehicle, and the Urban Forced Lange Change. For each scenario the autonomous features of all fully dynamic traffic vehicles (represented as blue vehicles in chapter 3) were varied to analyze how they would affect safety and traffic efficiency. The traffic vehicles' level of automation was varied between Level 0 (AEB only) and level 2 automation (lateral & longitudinal control). Level 2 vehicles also had a higher degree of variability, changing the time gap distance of the enabled ACC from 2 seconds to 1 second. This variability for the traffic vehicles was done in the highway environment for each interchange area, while in the urban it was based on each lap around the desired route. As was mentioned in chapter 3, the level of service (LOS) of the traffic was also varied, with the first half of each track having LOS A, and the second half being LOS D. For these experiments a total of 2 drivers ran each scenario once with no automation and then repeated the the Highway Forced Lane Change with ACC enabled. Table 2 details the structure by which the LOS, level of automation and ACC time gap of the traffic vehicles were varied at each respective driving scenario.

Scenarios	LOS	Section (IN /UL)	Traffic Automation	ACC time gap
HF HF* HM UF	A	1	L0	-
		2,3	L2	2 s
		4,5		1 s
	D	6	L0	-
		7,8	L2	2 s
		9,10		1 s

Table 2: Design of Experiments. (HF – Highway Forced Lane Change, HF* - Highway Forced Lane Change w/ driver ACC enabled, HM – Highway Merging Vehicle, UF – Urban Forced Lane Change, IN – Interchange, UL – Urban Lap).

For each experiment, the human drivers were given minimal instruction so as to not influence their behavior. Overall, they were instructed to follow the guiding vehicle to the best of their abilities while maintaining an adequate speed that would be below or equal to the speed limit of either the highway or urban road. The human subjects were also told to follow all traffic regulations that are specific for each environment based on the laws and regulations of the state of Texas. For the scenario in which the driver had ACC enabled, they were given additional instructions to maintain ACC applied at all times. They were to use the steering switches to change their desired distance and set speed and only use either the brake or throttle in case of emergencies.

PERFORMANCE METRICS

There is an expectation that AVs will bring a number of improvements to the transportation system, but it is unclear to what extent these benefits will be. This study attempted to gain insight into how AVs will improve traffic by using key metrics typically used to determine the safety and efficiency of vehicles and traffic.

Safety is a top priority throughout all interested parties, and it is widely assumed that the integration of more AVs into traffic will improve it. This is because AVs are expected to decrease human involvement in driving maneuvers and therefore reduce error. To verify that AVs are in fact improving the safety of traffic, it is crucial to analyze the safety performance of the various levels of automation. The most widely used metric is Time-To-Collision (TTC), which is described as the amount of time remaining before a vehicle collides with a pending object if it continues on its current trajectory. This value is calculated as follows:

$$TTC = \frac{X_{i-1} - X_i}{V_i - V_{i-1}}$$

Were $X_{i-1} - X_i$ is the relative distance from the ego vehicles to the preceding vehicle and $V_i - V_{i-1}$ is the relative velocity. The TTC value can be used to derive more detailed safety metrics, such as time exposed time-to-collision (TET), which is the amount of time a vehicle remains under a minimum safety TTC threshold, and time integrated time-to-collision (TIT), which weights the level of safety by taking into how small the TTC value becomes. The TET value can be calculated by the following way:

$$TET = \sum_{t=0}^{T} \delta_i(t) * \tau$$

were i is the respective vehicle being analyzed, τ is a time step, and $\delta_i(t)$ is equal to 1 if TTC is below a give minimum safety threshold and 0 otherwise. TIT can be obtained as follows:

$$TIT = \sum_{i=1}^{N} \int_{0}^{T} [TTC^{*} - TTC_{i}(t)]dt$$

were TTC* represent the minimum safety threshold value.

Traffic efficiency is another area that AVs are meant to improve by reducing human error and eliminating unnecessary maneuvers that are detrimental to the flow of traffic. A good indicator to view how well traffic flows is to analyze the velocity and acceleration of each vehicle, as well as the headway distance. By doing so we can gain an insight into how good traffic vehicles move, given that in an ideal situation the most effective traffic flow will have no disturbances and travel at a constant velocity with the smallest possible headway distance, which would allow for a higher density of traffic vehicles.

RESULTS AND DISCUSSION

The results found through the experiments are divided for each driving scenarios as shown previously in Table 2, with HF and HF* being combined to compare the performance of human drivers with ACC enabled versus driving the vehicle manually.

Highway: Forced Lane Change

The box plots below in Figure 18 and 19 show the values obtained for human driver 1 and 2, respectively, with no automation. Within each figure the box plots are divided for each section in which the force lane change needed to be performed. The colors of the box plots represent the traffic's level of automation and ACC time gap value, with black being for Level 0 (AEB only), blue being level 2 with time gap of 2 seconds, and red being level 2 with time gap of 1 second.

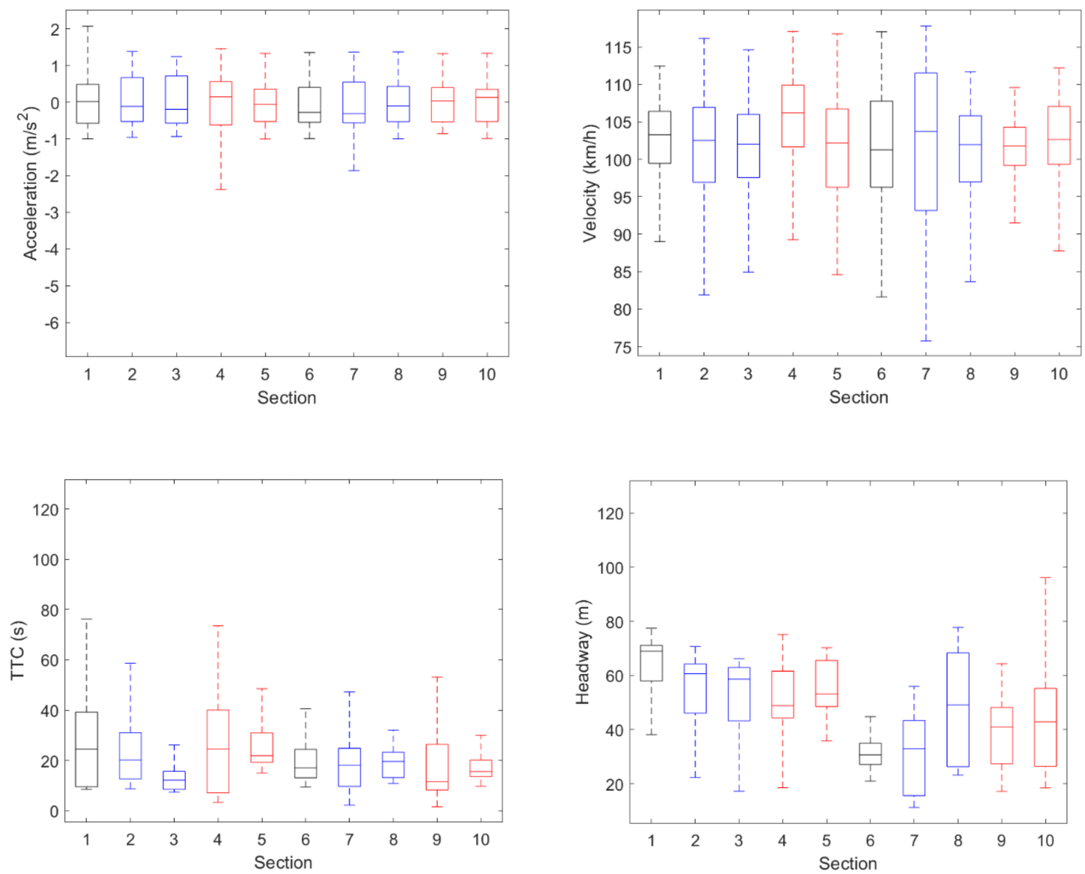

Figure 18: HF – Driver 1 values for each Interchange Maneuver (From Top Left: Acceleration, Velocity, TTC, Headway). Note – BLACK: L0 Traffic, BLUE: L2 Traffic w/ time gap = 2 s, RED: L2 Traffic w/ time gap = 1 s

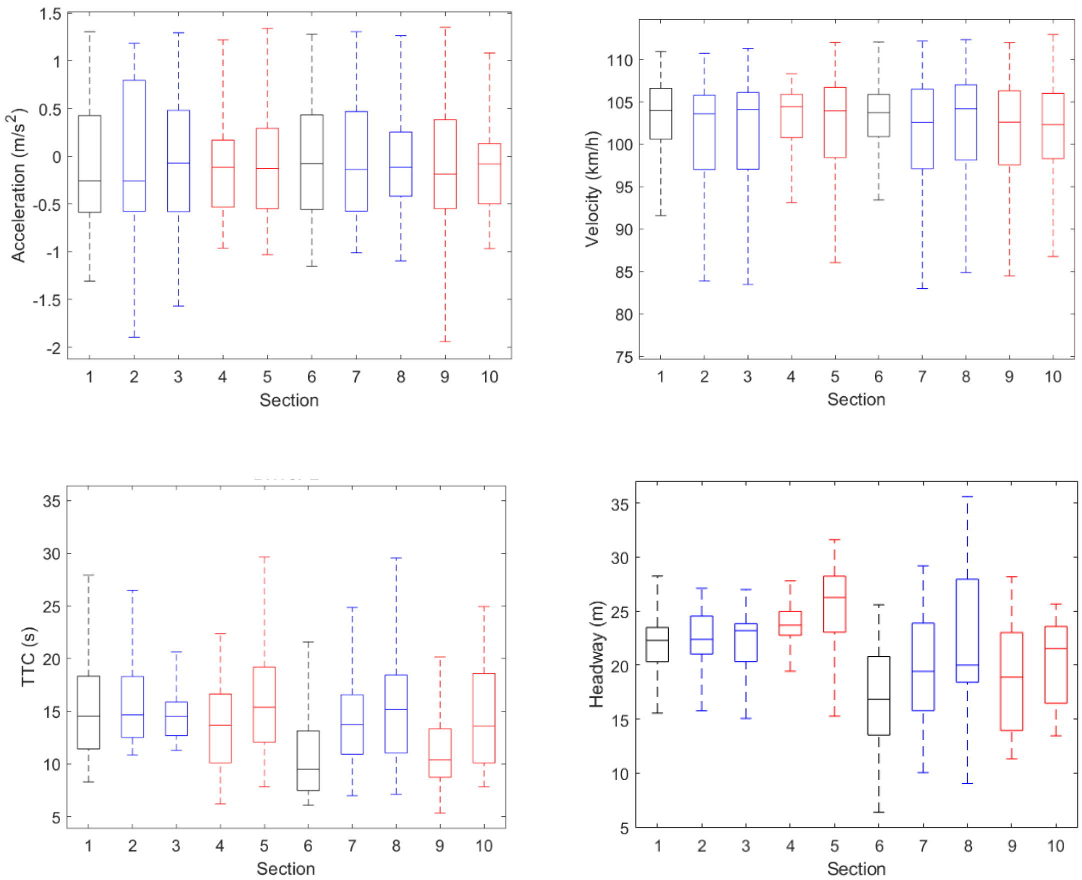

Figure 19: HF – Driver 2 values for each Interchange Maneuver (From Top Left: Acceleration, Velocity, TTC, Headway). Note – BLACK: L0 Traffic, BLUE: L2 Traffic w/ time gap = 2 s, RED: L2 Traffic w/ time gap = 1 s

As was to be expected, the results for the human drivers without ADAS capabilities in the highway forced lane change scenario show no profound differences between each interchange. With both drivers in full control over the vehicle, constant driving behavior is maintained. This can be seen with the parity in each box plot, specifically for velocities, which remain near a speed 65 mph (105 km/h) throughout the entire track. There does seem to be a difference in the headway distance between the first 5 interchanges (section 1-5) and the remaining 5 (section 6-10). This was also to be expected as the traffic was designed to maintain a headway distance defined by LOS A (146 m) for the first 5 interchanges. This allowed the driver to maintain a larger headway distance from the guiding vehicle but had to accept a lower headway distance for sections 6 through 10, being that in these interchanges the traffic was designed to maintain LOS D headway of 46 m.

When analyzing the performance of the drivers when ACC was enabled, the results seem to show that each driver encountered a dangerous situation at some point in the experiment, with Driver 1 actually losing complete control during one forced lane change. The results for both Driver 1 and 2 with ACC enabled is shown below in Figure 20 and 21, respectively.

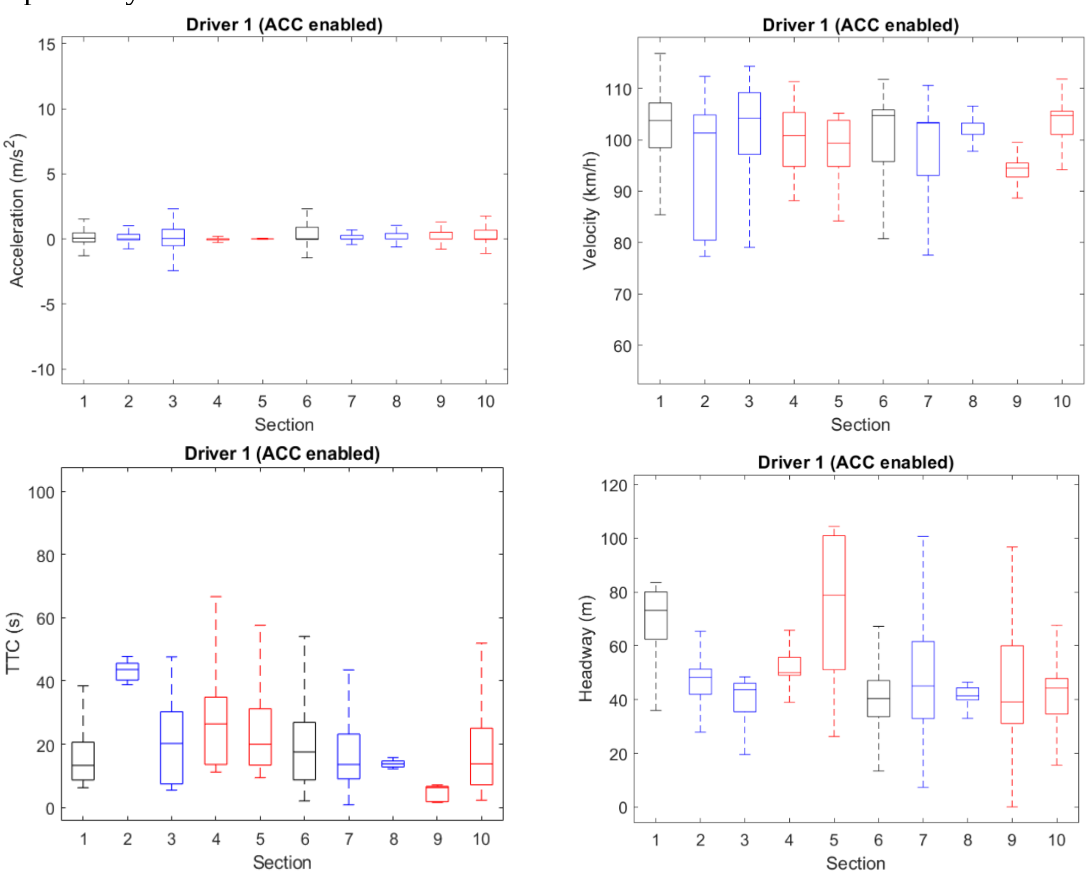

Figure 20: HF* – Driver 1 values for each Interchange Maneuver (From Top Left: Acceleration, Velocity, TTC, Headway). Note – BLACK: L0 Traffic, BLUE: L2 Traffic w/ time gap = 2 s, RED: L2 Traffic w/ time gap = 1 s

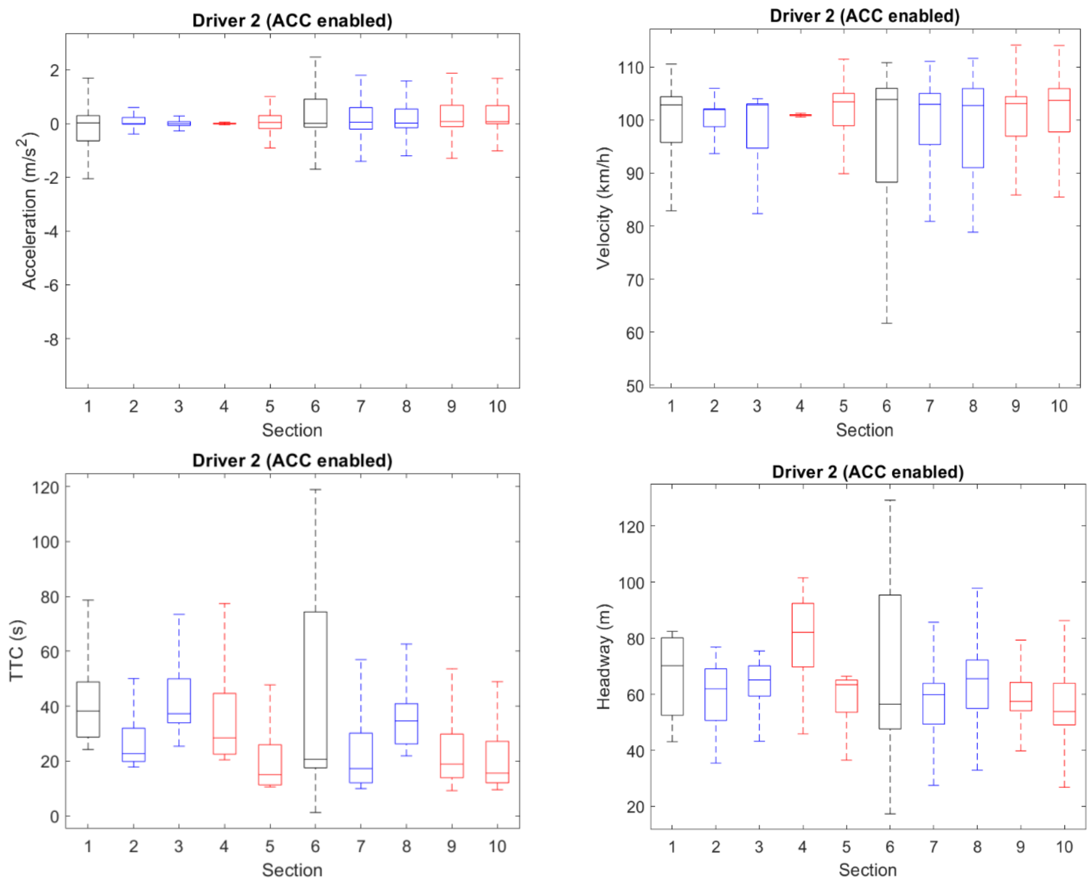

Figure 21: HF* – Driver 2 values for each Interchange Maneuver (From Top Left: Acceleration, Velocity, TTC, Headway). Note – BLACK: L0 Traffic, BLUE: L2 Traffic w/ time gap = 2 s, RED: L2 Traffic w/ time gap = 1 s

Although difficult to notice in the box plots for Driver 1, they lost control in section 8 when performing the forced lane change while possessing ACC. To more clearly see the loss of control that Driver 1 encountered, the resulting values for section 8 are highlighted below in Figure 22. As shown, the TTC value dramatically reduces to near zero and at that particular moment a brake output of above 50% is applied to the vehicle, causing it to lose control. The reason for this immediate reduction in TTC value is most likely due to a sudden step change in the headway distance as the detected target vehicle changes from the guiding vehicle to that of a traffic vehicle originally traveling along the main lanes.

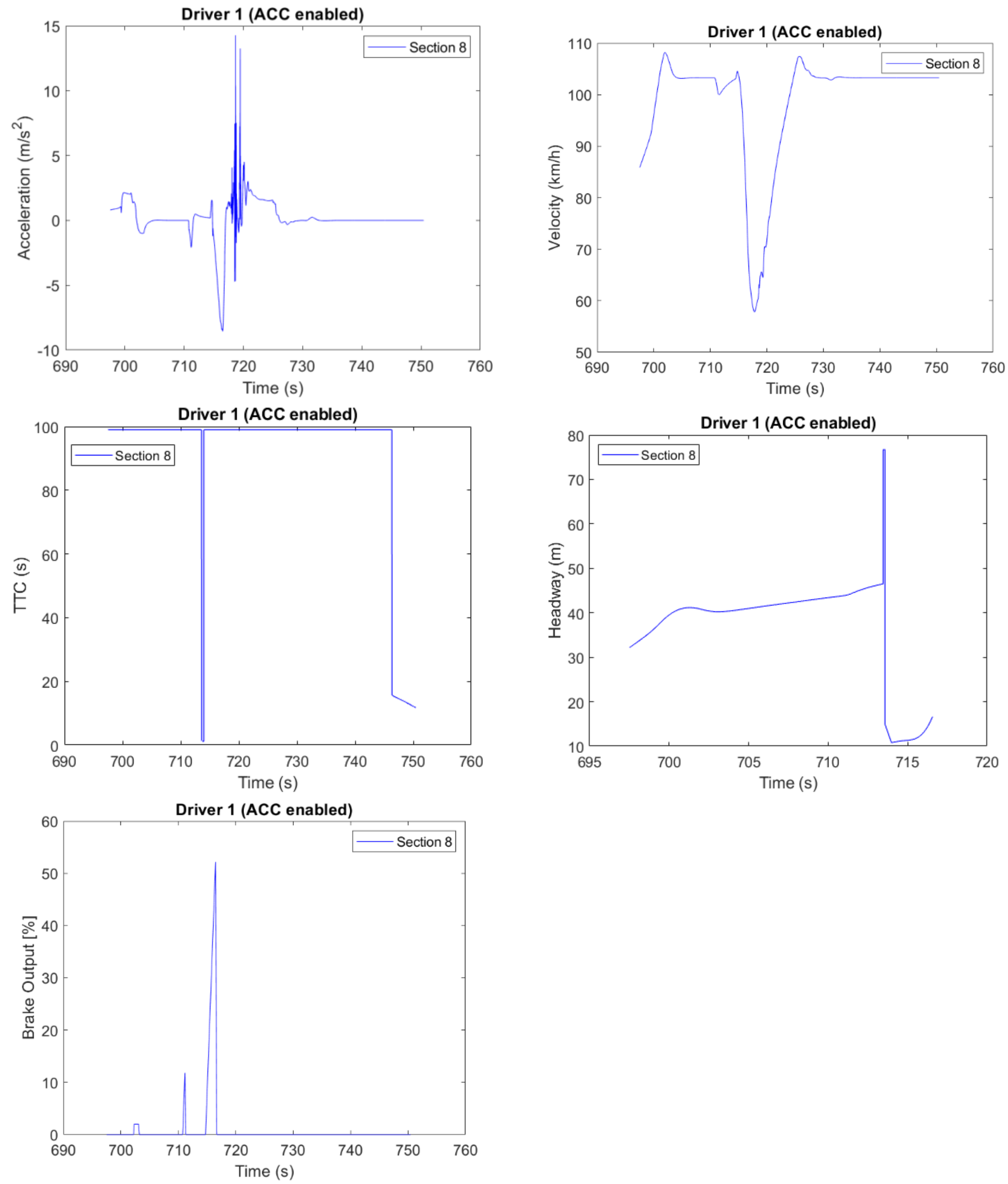

Figure 22: HF* – Driver 2 values for Interchange 8 (From Top Left: Acceleration, Velocity, TTC, Headway, Brake Output).

Driver 2 also encounters a similar situation but in section 6. This can be slightly noticed in the box plots shown in Figure 21, as the ones for section 6 seems to differ from all others with an extended box plot. Again, to clearly see this situation, we highlight the values for section 6, as shown below in Figure 23.

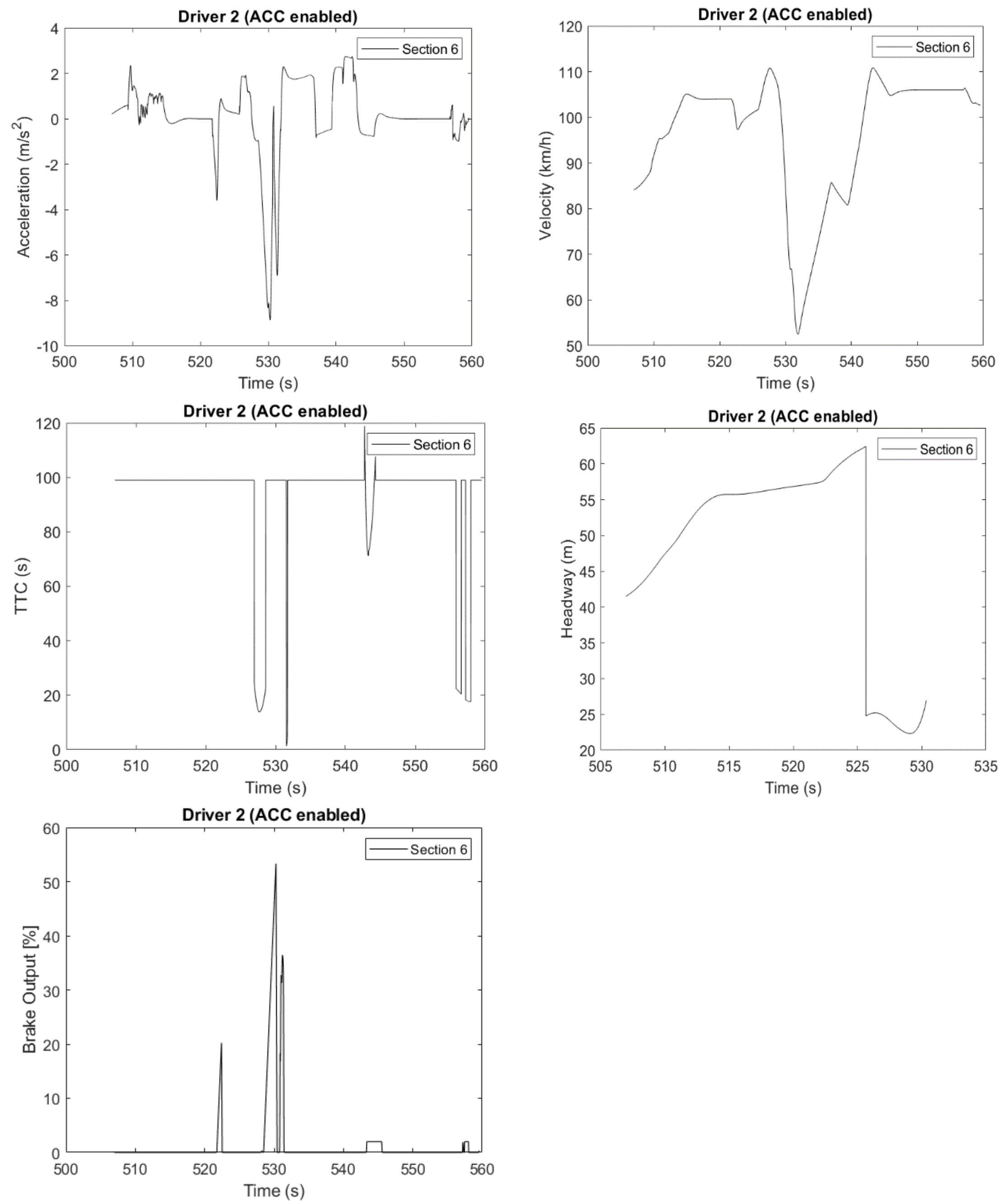

Figure 23: HF* – Driver 2 values for Interchange 8 (From Top Left: Acceleration, Velocity, TTC, Headway, Brake Output).

Similar to what happened with driver 1, driver 2 experiences a sudden step change. This again occurs as the driver is forced to merge into the main lanes and the detected target vehicle changes from the guiding vehicle to that of a traffic vehicle that was originally traveling along the main lanes. This sudden step change in headway distance leads to a rapid decline in the TTC value and an immediate brake output of over 50%, which causes the driver to momentarily lose control.

To continue the comparison of a driver's performance with both a manually driven vehicle and an ACC enabled one, we look in detail to the TTC values to determine if safety was affected by ACC. From the table below, the minimum TTC values, the Time Exposed TTC (TET) and the Time Integrated TTC (TIT) are shown. To calculate TET and TIT the minimum safety TTC threshold value of 3 seconds was used. Although a lower TTC threshold value can be used for ADAS driven vehicles, given that they are more equipped to avoid unsafe situations, a value of 3 s was chosen as it the most common value used in literature and it would be inclusive of all possible unsafe situations.[36] From the table, it can be seen that for both Driver 1 and 2, the minimum TTC values increase when ACC is enabled but only during LOS A traffic. During LOS D traffic the minimum TTC values are shown to increase, meaning that it could be argued that for LOS D traffic, enabling ACC results in a more dangerous driving situation. This is evident by analyzing TET and TIT. Both values are shown to increase from a manually driven vehicle to one that is using ACC. This means that during the LOS D traffic, the drivers spent more time under the minimum unsafe threshold TTC value of 3 s while using ACC, and with an increase in TIT, the driver spent more time at values closer to zero. Now this may be explained by fact that an ACC

[36] Minderhoud and Bovy. "Extended time-to-collision measures," 2000.

will allow for lower TTC values, as it is attempting to optimize lowest possible distance, given that it is capable of implementing a quicker response to prevent a collision.

	LOS A			LOS D		
	TTCmin	TET	TIT	TTCmin	TET	TIT
Driver 1	3.430	0	0	1.672	0.76	0.633
Driver 1 ACC	5.455	0	0	0.842	1.82	2.276
Driver 2	9.370	0	0	6.346	0	0
Driver 2 ACC	24.21	0	0	1.280	0.1	0.109

Table 3: Comparison of TTC values (TTCmin – minimum TTC, TET – Time Exposed TTC, TIT – Time Integrated TTC).

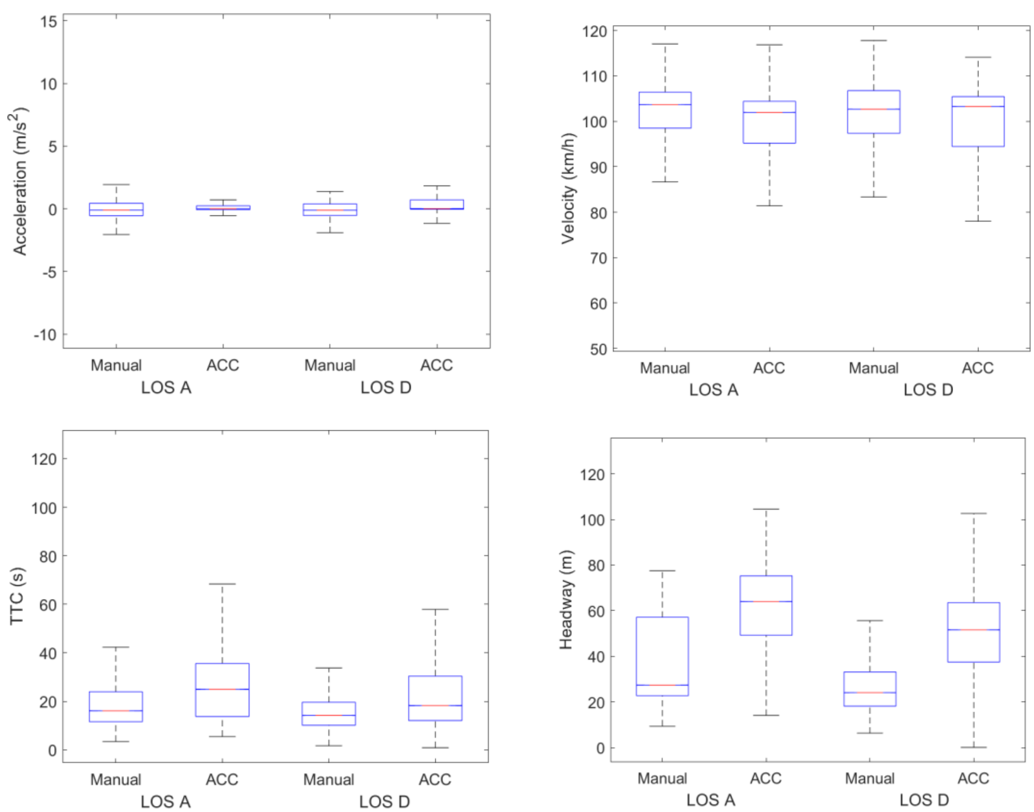

Figure 24: Comparison between Drivers with no automation and ACC enabled. (From Top Left: Acceleration, Velocity, TTC, Headway).

When comparing the results for each type of driver we can see that ACC does seem to improve safety and traffic efficiency. In Figure 24 we directly compared the values of each driver type. From the plots it can be seen that from manual to ACC, both TTC and headway distance are increased. This assures us that overall, the safety does seem to improve with ACC. Now, when comparing only the values of ACC, it was noticed that for LOS D traffic a decrease in TTC and headway was produced. A similar pattern was seen in both acceleration and velocity, were the variability in these values is decreased when using ACC, meaning a more constant motion. When comparing ACC between LOS A and LOS D traffic, there seems to be more variability in LOS D. This can mean that although ACC is able to improve driving performance and safety its value is drastically reduced in high density traffic and could pose a greater risk, as was the case in which both drivers encountered a sudden step change in headway distance and lost control.

Now, to understand how ADAS affects the overall performance of traffic, we analyzed the effects that both driver types would have on their respective traffic environment. The results for each situation, either a driver with no automation or with ACC enable, are shown in Figures 25 and 26, respectively. As was previously mentioned, the traffic vehicles in all scenarios varied in the level of automation that they possessed, either having only AEB, or level 2 automation with a different time gap for ACC. From the data, it seems that the most influential parameters that affect the performance of the traffic is the level of service, and time gap. The type of driver seemed to have the same influence regardless whether ACC was enabled or not. As was to be expected, the overall performance of the traffic is reduced drastically with a change to LOS D. With the more congested traffic, the variability in acceleration and velocity is increased, signaling that traffic is incapable of maintaining a constant speed and frequently stops. For TTC and headway, the values of the entire traffic are shown to decrease in LOS D, which again is to be expected, given that the higher destiny reduced the distance between vehicles. As for the time gap of the ACC, it seems that a lower value has no effect on the efficiency of traffic as it appears to not cause a change in acceleration or velocity, but it does seem to decrease safety. From the figures, it can be seen that traffic vehicles with a time gap of 1 s have a lower TTC value when compared to that of a time gap of 2 s. In fact, the performance of an ACC with a time gap of 1 second are nearly equal to vehicles with only AEB.

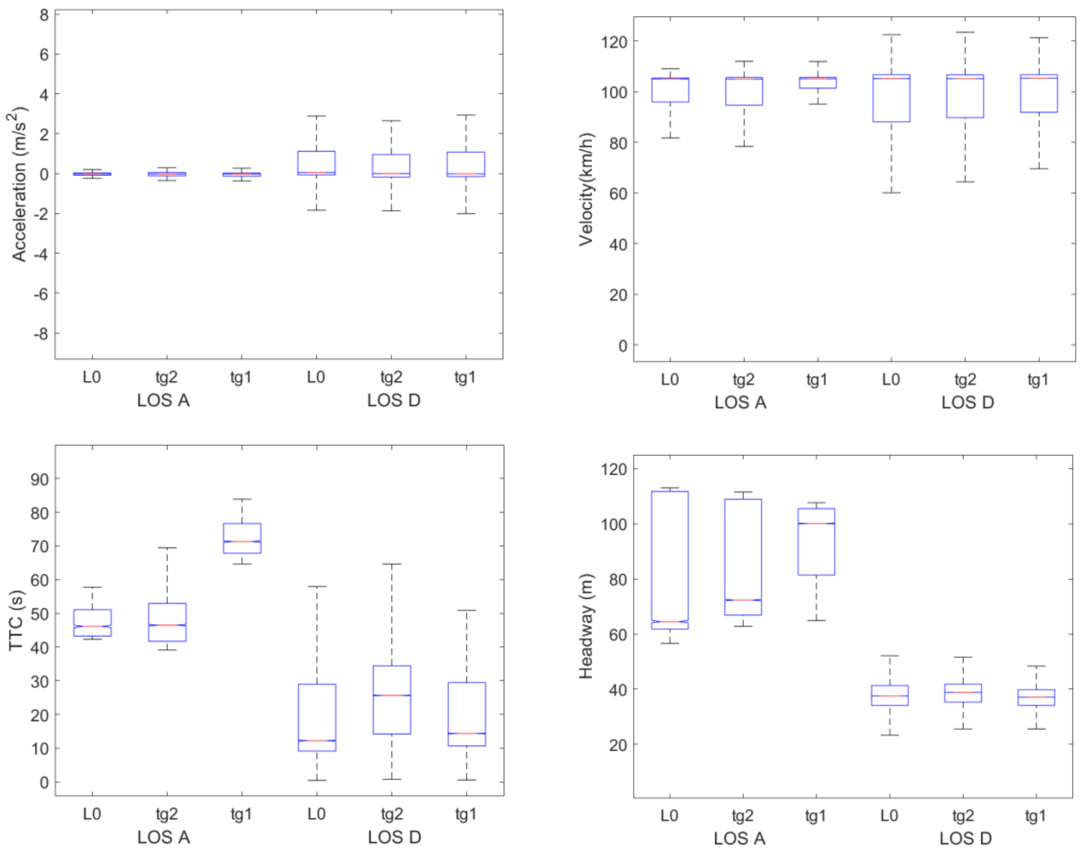

Figure 25: Results of Traffic Vehicles in the Highway Forced Lane Change Scenarios with Drivers having no automation (From Top Left: Acceleration, Velocity, TTC, Headway). Note: L0 – No Automation, tg2 – time gap = 2 s, tg1 = time gape = 1 s.

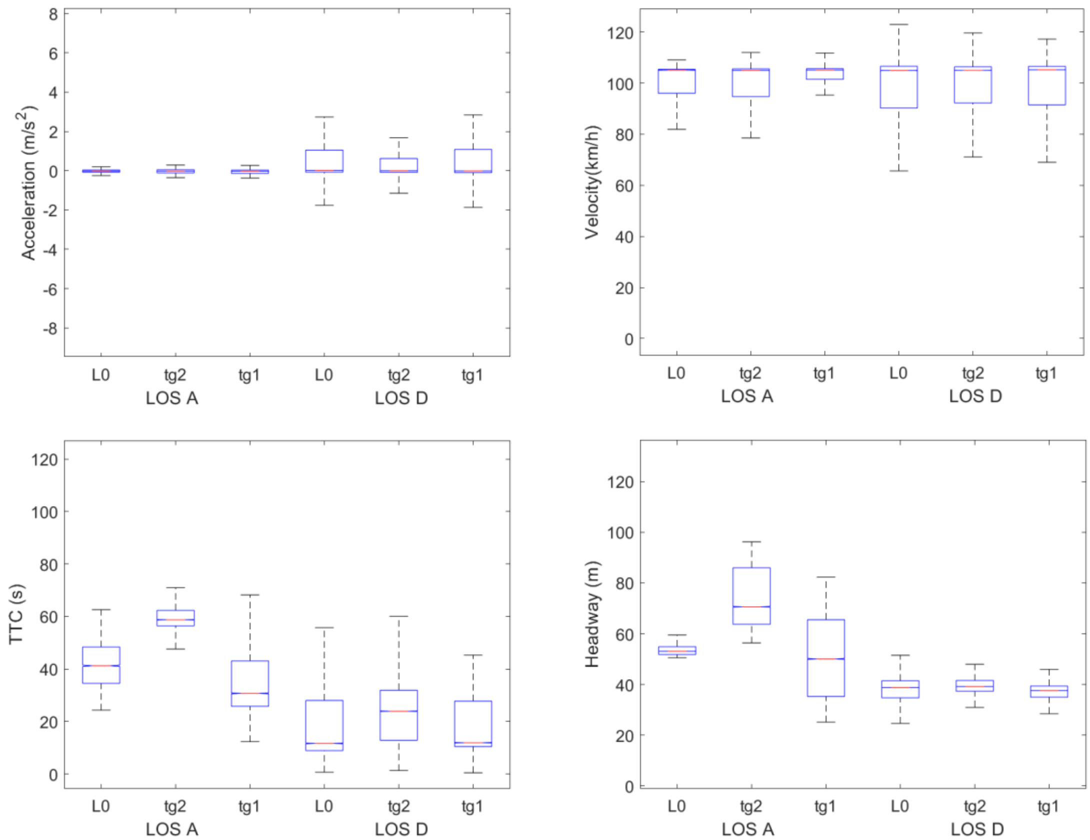

Figure 26: Results of Traffic Vehicles in the Highway Forced Lane Change Scenarios with Drivers having ACC enabled. (From Top Left: Acceleration, Velocity, TTC, Headway). Note: L0 – No Automation, tg2 – time gap = 2 s, tg1 = time gape = 1 s.

Highway: Merging Vehicle – On-Ramp

For the second scenario in the highway environment the driver had no automation, while the traffic's level of automation varied. The results for the drivers in this scenario are shown below in Figure 27. Overall, there was no changes in the drivers performance through the entire track. In Figure 9 it can be seen that from LOS A to LOS D, the drivers still maintain a similar velocity and maintain an adequate distance from the traffic vehicles, which also resulted in a similar TTC value in both a free flow and congested traffic situation. It seems that the merging vehicle had no effect on either driver's performance, as they were able to properly vary their speed and distance to allow for the vehicle to safety merge ahead of them or increase their speed to avoid the merging vehicle from cutting in and forcing them to dramatically reduce their speed.

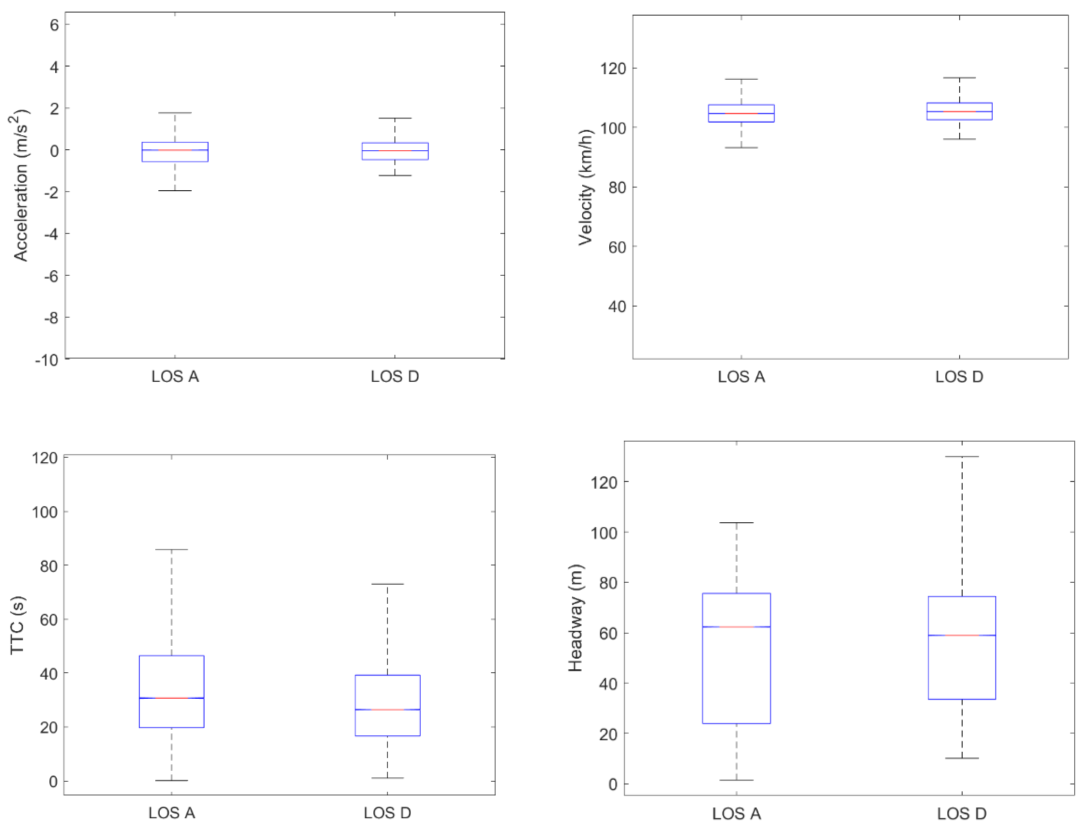

Figure 27: Results for Drivers in the Highway On-Ramp Mering Vehicle Scenario (From Top Left: Acceleration, Velocity, TTC, Headway).

The results of the traffic vehicles were also obtained, shown below in Figure 28. From the plots, it can be seen that the on-ramp merging vehicle had little to no effect on the performance of the overall traffic. This becomes obvious when looking at acceleration, which remain nearly constant at zero. This clearly shows that traffic vehicles maintain a constant velocity through the entire roadway and are never required to change speed. When looking at TTC values, it can be seen that for the most part, the entire traffic never encounters an unsafe situation. In fact, the TCC and headway values of vehicles in LOS A with either level 0 or ACC with time gap of 1 second were omitted because all vehicles maintained a large distance from one another, and therefore never produced a detectable headway distance and TTC value. For LOS D the performance for all vehicles is reduced and as was seen in the previous scenario, an ACC with at time gap of 1 s produces smaller TTC and headway distance values when compared to a time gap of 2 s.

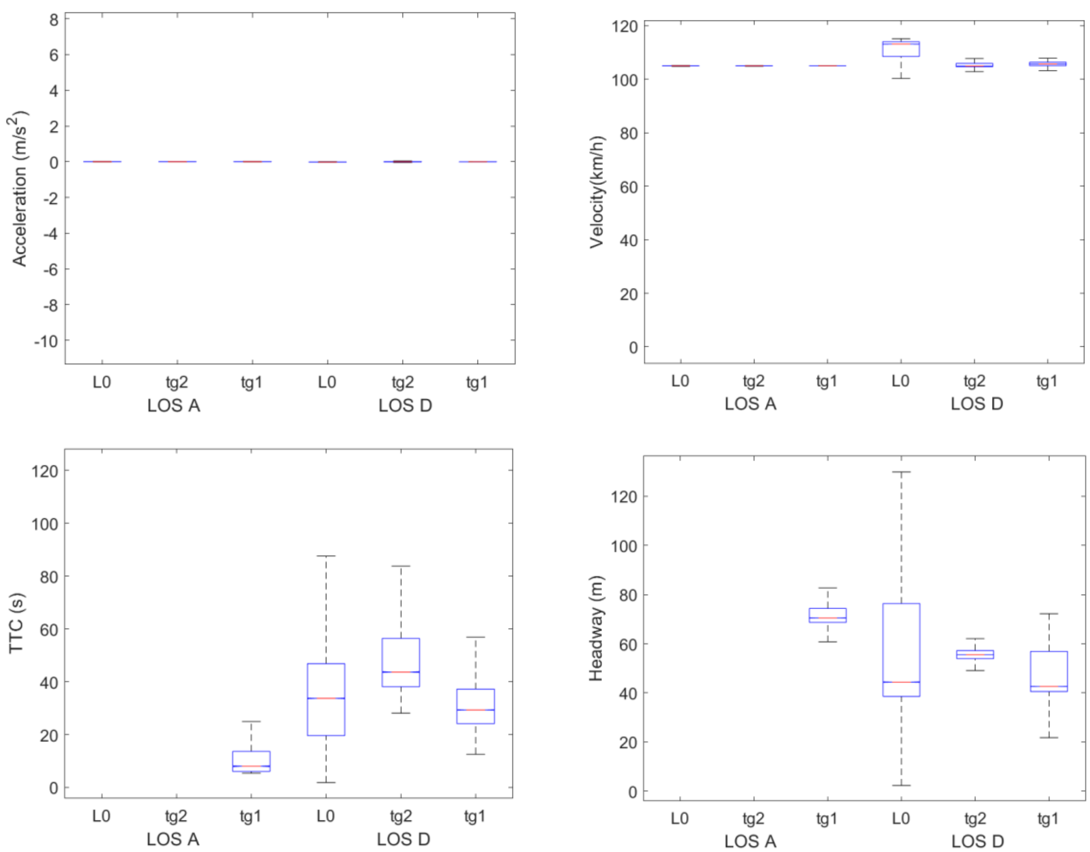

Figure 28: Results for Traffic Vehicles in the Highway On-Ramp Merging Vehicle Scenario (From Top Left: Acceleration, Velocity, TTC, Headway). Note: L0 – No Automation, tg2 – time gap = 2 s, tg1 = time gape = 1 s

Urban: Forced Lange Change

The results for the drivers and the traffic vehicles for the Urban Forced Lane Change Scenario are shown below in Figure 29 and 30, respectively. When analyzing the data obtained for the drivers, it can be seen that their performance is heavily influenced by the level of service. All the values obtained for the driver are reduced when traveling in LOS D traffic, excluding acceleration. This is to be expected in an urban environment, since LOS D signifies a reduced headway distance and velocity to accommodate for a higher density of vehicles.

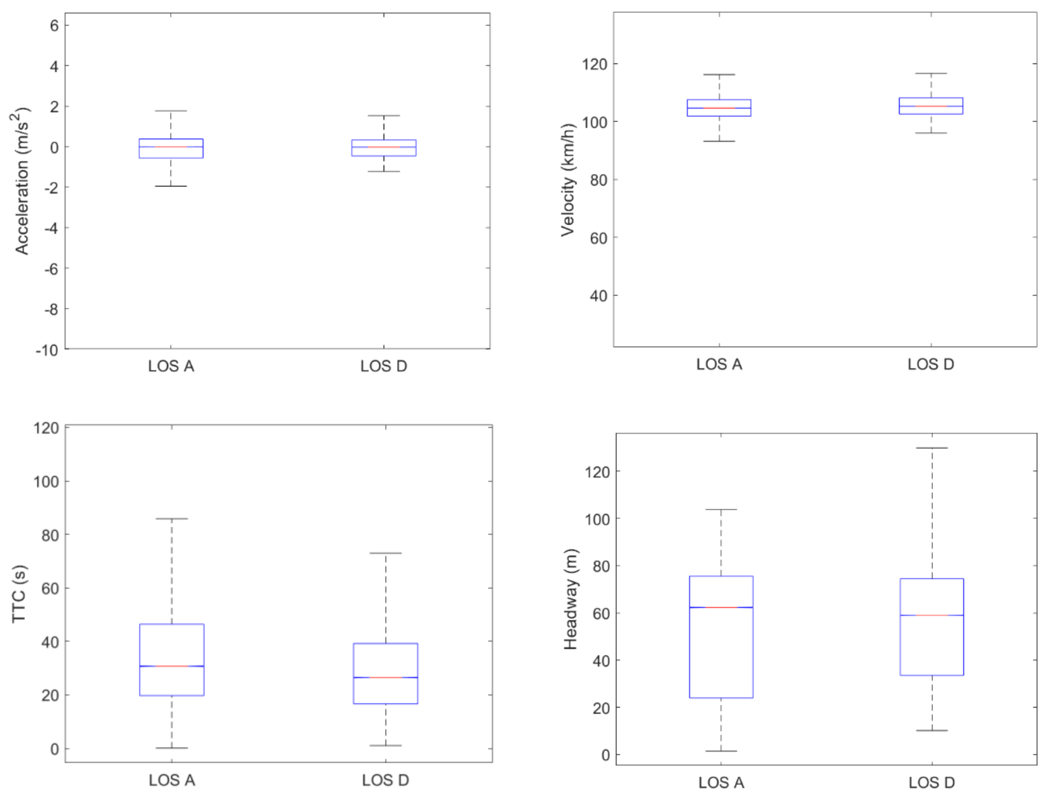

Figure 29: Results for Drivers in the Urban Forced Lange Change Scenario (From Top Left: Acceleration, Velocity, TTC, Headway).

When analyzing the performance of the traffic vehicles, it can be seen that ACC seems to slightly improve the traffic's flow. This is evident in the length of the box plots for acceleration and velocity, which become smaller with ACC enabled and therefore signify a reduction in the common stop-and-go motion that is prevalent in urban roadways. The time gap parameter also seems to have an effect with the performance of the traffic as it can be seen to reduce the range of acceleration and velocity. This is most likely due to the reason that with a smaller time gap the traffic vehicles become less sensitive to the smaller headway distances of urban driving, effectively reducing the frequency of braking. Now, although the reduced time gap seems to improve traffic efficiency in the urban environment, it seems to have no effect on safety, as the TTC value for time gap of 2 seconds and 1 second are nearly identical.

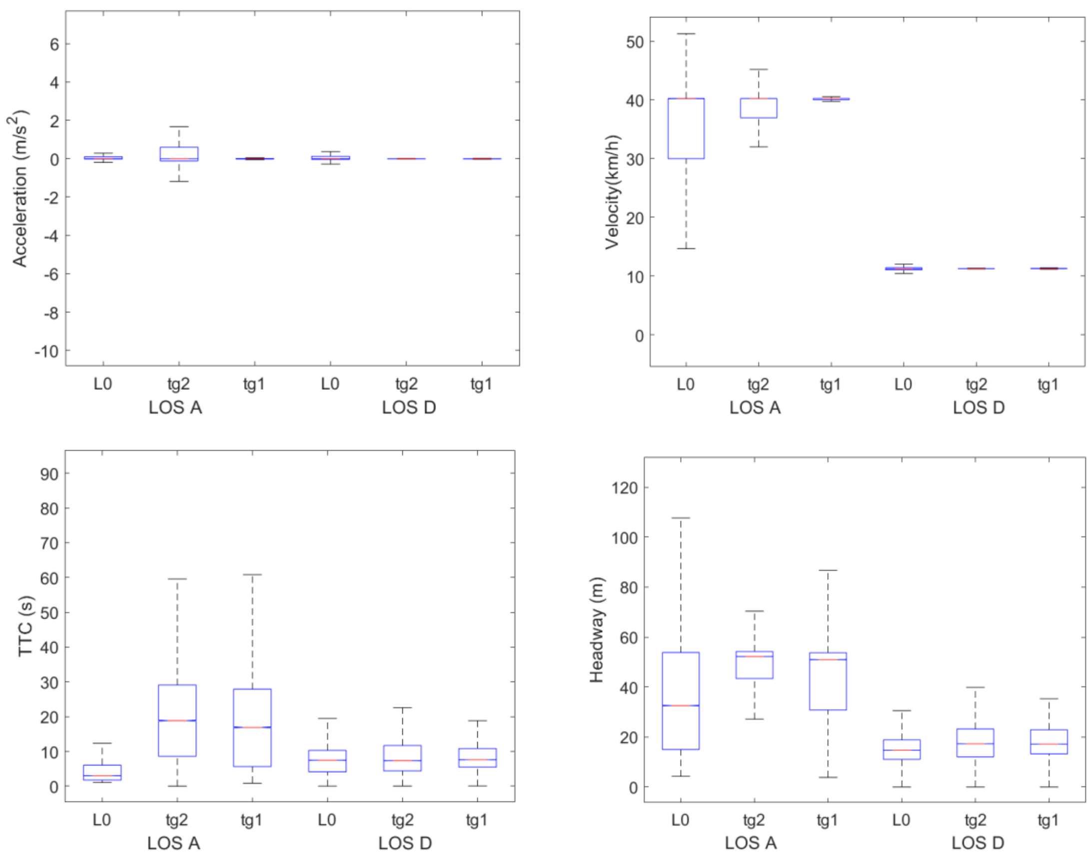

Figure 30: Results for Traffic Vehicles in the Urban Forced Lange Change Scenario (From Top Left: Acceleration, Velocity, TTC, Headway). Note: L0 – No Automation, tg2 – time gap = 2 s, tg1 = time gape = 1 s.

CONCLUSION

The preliminary Driver-In-the-Loop experiments were used to analyze how vehicle automation would perform in different roadway environment and driving scenarios. For this study, we analyzed level 1 and level 2 automation in both a highway and an urban roadway, while also implementing a distinct driving scenario, either a forced lane change or an on-ramp merging vehicle. The data seems to hint that an increase in level of automation might have a positive effect on traffic performance and/or safety for all environments and driving scenarios, specifically for higher levels of service traffic flow. For more congested traffic, the performance of the tested ADAS was reduced when compared with a free flow traffic and showed to be less safe than that of a manual driver. This was noticed by how the human drivers encountered an unsafe situation at least once and both lost control of the vehicle. The data showed that this was caused by a sudden step change in the detected headway distance. In this particular situation the ACC vehicle might pose a bigger risk, but more testing involving a higher quantity of human subject will need to be performed to verify this claim.

Overall, the data obtained from the preliminary experiments seems to suggest that a higher level of automation might improve the performance of each vehicle in terms of traffic safety and efficiency for highway and urban roadways. Although this might be true, the data also showed that lower levels of automation could possibly result in a higher level of risk for human drivers. To reach a definitive conclusion regarding the benefits and risks of AVs in different environments and driving scenarios more testing involving a variety of human participants will need to be conducted. For now, the preliminary experiments help verify the feasibility of the simulation framework and will allow the developed virtual environments to be used for future human subject studies.

Chapter 7: Future Work

The study has shown how AVs perform in various environments and driving scenarios and the findings will help improve our understanding of ADAS to ease their incorporation into traffic. Nonetheless, there is still much research to be done on this emerging technology. As has been mentioned throughout this thesis, before the development of Level 5 AVs we will go through a mixed traffic phase. This will involve different levels of automated vehicles and human drivers interacting in different environments and driving scenarios. For that reason, it is imperative to continue analyzing the performance of AVs in various situations to continue developing their ODD framework.

An area that needs to be investigated more is how AVs perform in different environments. For this study we prioritized a highway with an X-Configuration interchange but there are various other structures that could be used to analyze different situations. For example, a weaving interchange, which is a variation of the X-Configuration, can be used to analyze AVs. The Weaving interchange differs from the X-Configuration by having an auxiliary lane that gives drivers more room to accelerate or decelerate when entering or exiting an on-ramp. There are also other variations of the diamond interchange that can be implemented in the highway road. They include the conventional, stacked, split, or spread diamond, all seen below in Figure 31.

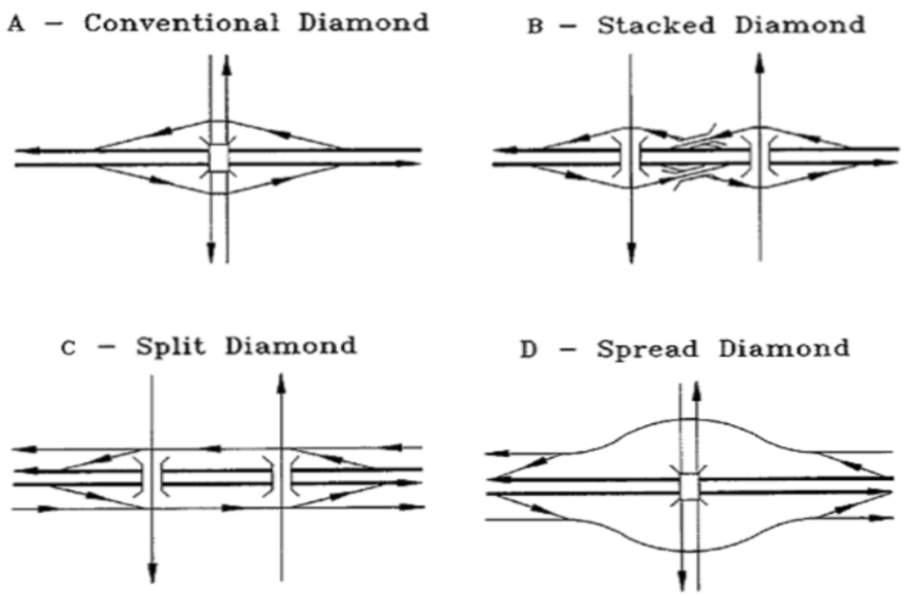

Figure 31: Variations of the Diamond Interchange.[37]

For the urban environment there is even more work that can be done to analyze an AV's performance. There are countless driving scenarios that will lead to a better understanding. Some examples include the analysis of AVs with Right Turn Only lanes, Bus dwell sections, or on-street parallel parking. It is also necessity to analyze AVs at intersections with different configuration of traffic lights. Most importantly, urban environments involve a high amount of human and vehicle interactions, therefore, it is crucial to analyze how AVs perform with pedestrians and cyclists in a mixed traffic scenario.

Another key area of research is to analyze higher levels of autonomous vehicles, mainly level 3 and 4 AVs. Companies such as Honda and Audi have begun deploying Level 3 AVs into the Japanese market, with restrictions due to legislation, and by 2021 Hyundai Motors Co., Kia Motors Co., BMW, and Mercedes-Benz are projected to have level 3 AVs

[37]TxDOT Roadway Design Manual.

available for purchase.[38] There is an urgency to properly understand level 3 and 4 AVs as more companies deploy their own version and diversify the configuration of traffic. A proper analysis of the mixed traffic scenario should involve all levels of automation and varying percentages to analyze how each configuration of a mixed traffic scenario will affect safety and efficiency. Also, with added levels of AVs it would be ideal to compare a true mixed traffic with one that has regions exclusively for AVs only, such as a dedicated AV lane. With this type of research, a clearer understanding of what are the capabilities of all levels of AVs will be established and we will be able to make the necessary changes to our current infrastructure and regulations to maintain a safe environment for humans, whether they are inside of a manually-driven vehicle, an AV, or neither.

[38] IEEE, "New Level 3 Autonomous Vehicles Hitting the Road in 2020," 2020.

Appendix

The following figures show the visual representation of the virtual highway and urban environments that were designed to test the performance of AVs.

Figure 32: Highway Advanced Exit Sign

Figure 33: Highway Exit Sign

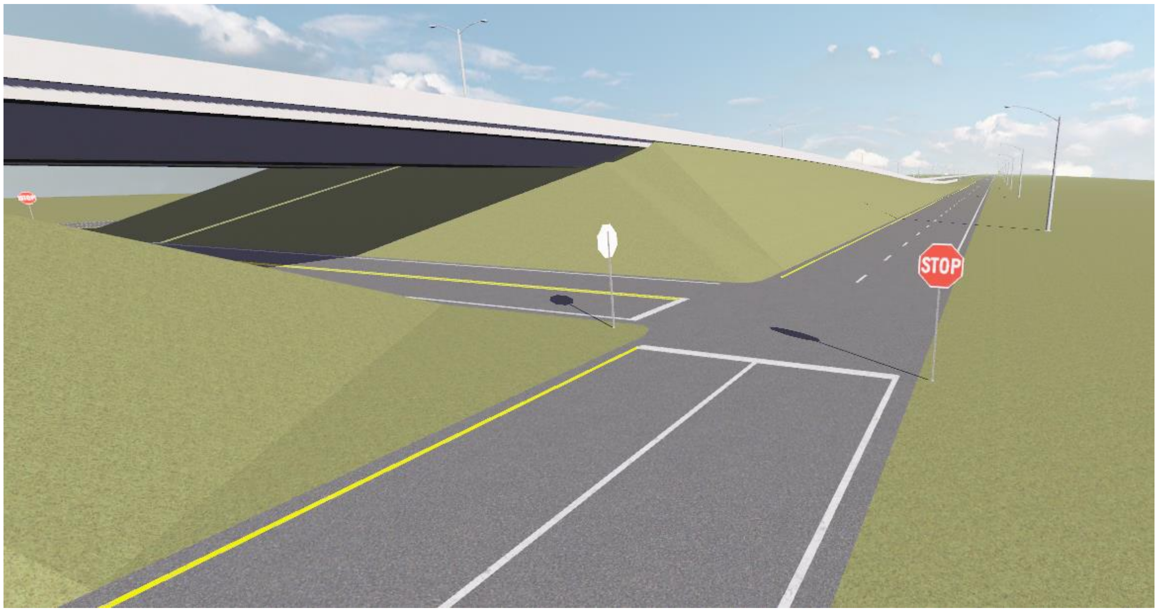

Figure 34: Highway Frontage Road and Overpass

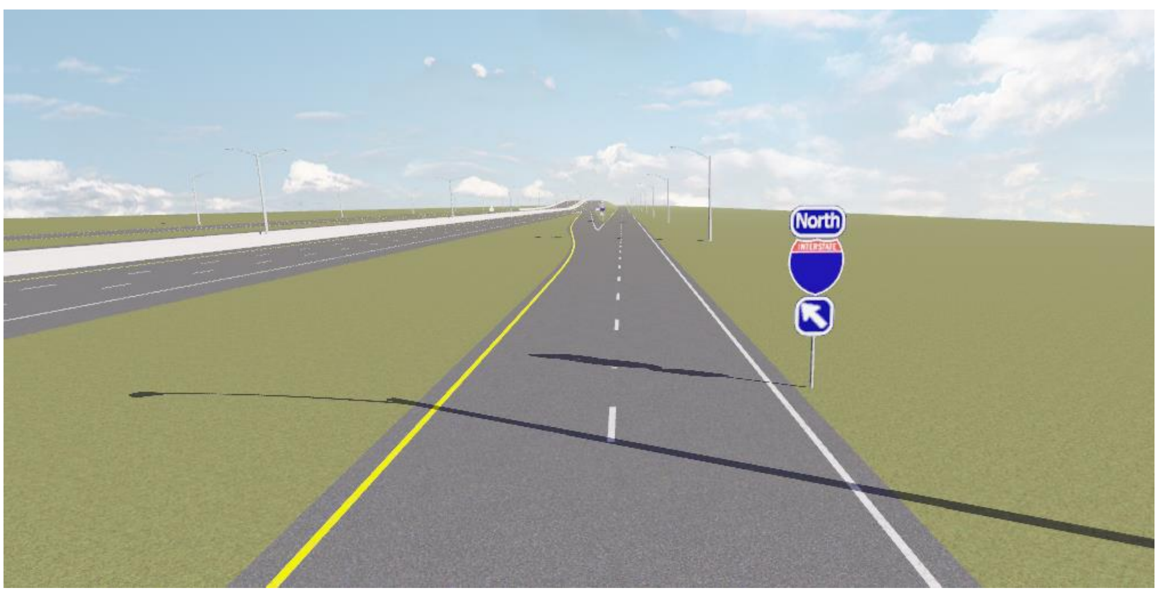

Figure 35: Highway Entrance Sign

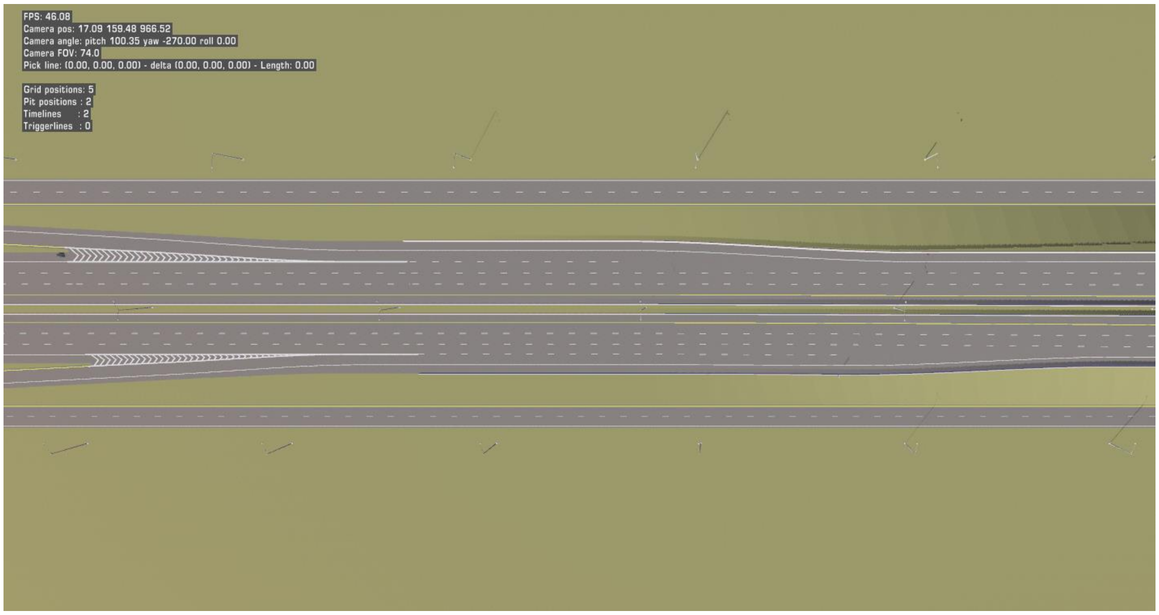

Figure 36: Ariel View of Highway Entrance and Exit Ramp Tapers.

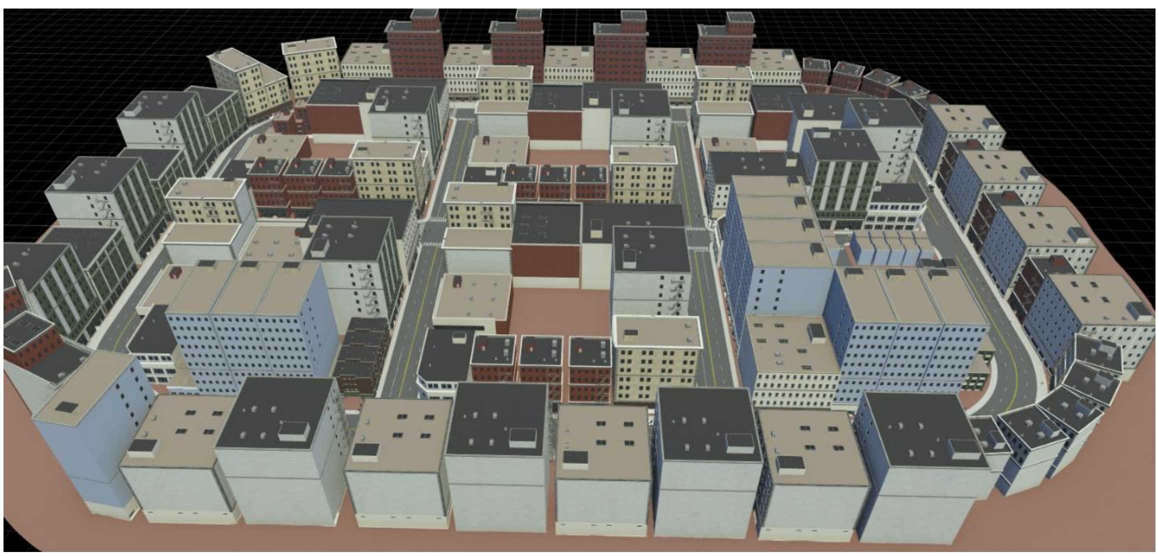

Figure 37: Overview of Complete Urban Environment.

Figure 38: Construction Zone

Figure 39: Bus Dwell Area.

Figure 40: Ariel View of Bus Dwell Area.

Figure 41: Bus Stop Area with halted Transit Bus.

Figure 42: Mid-Block Driveway.

Figure 43: On-road Parallel Parking

Figure 44: Right Turn Only Lane

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